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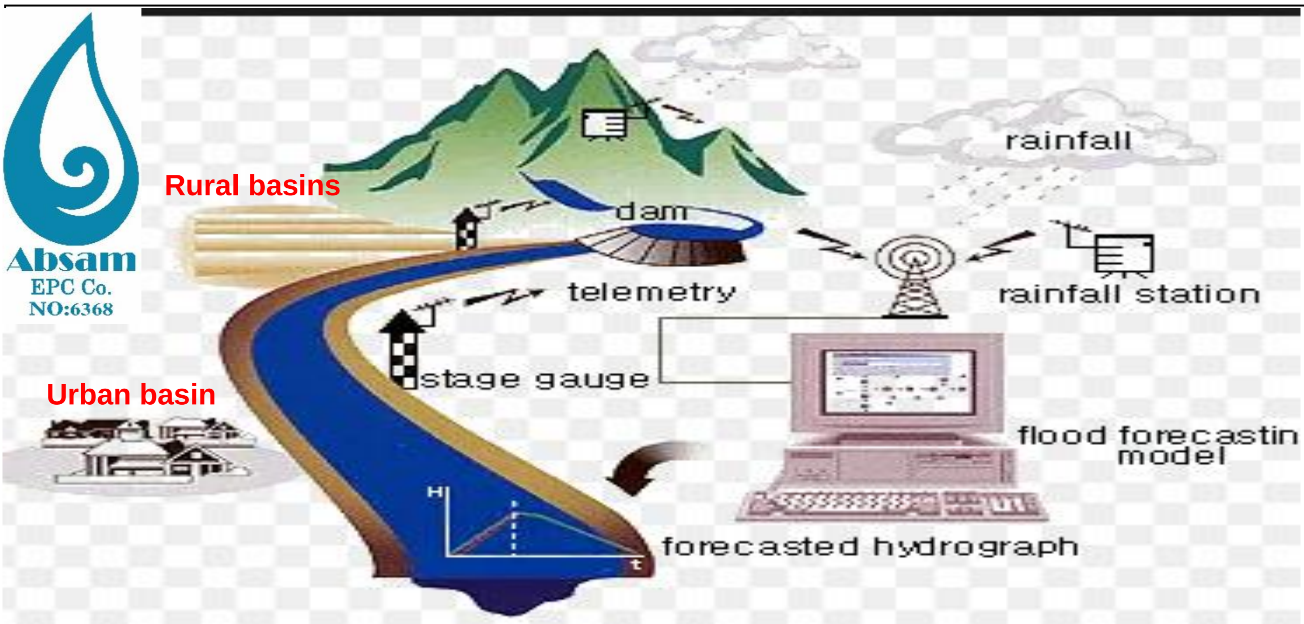

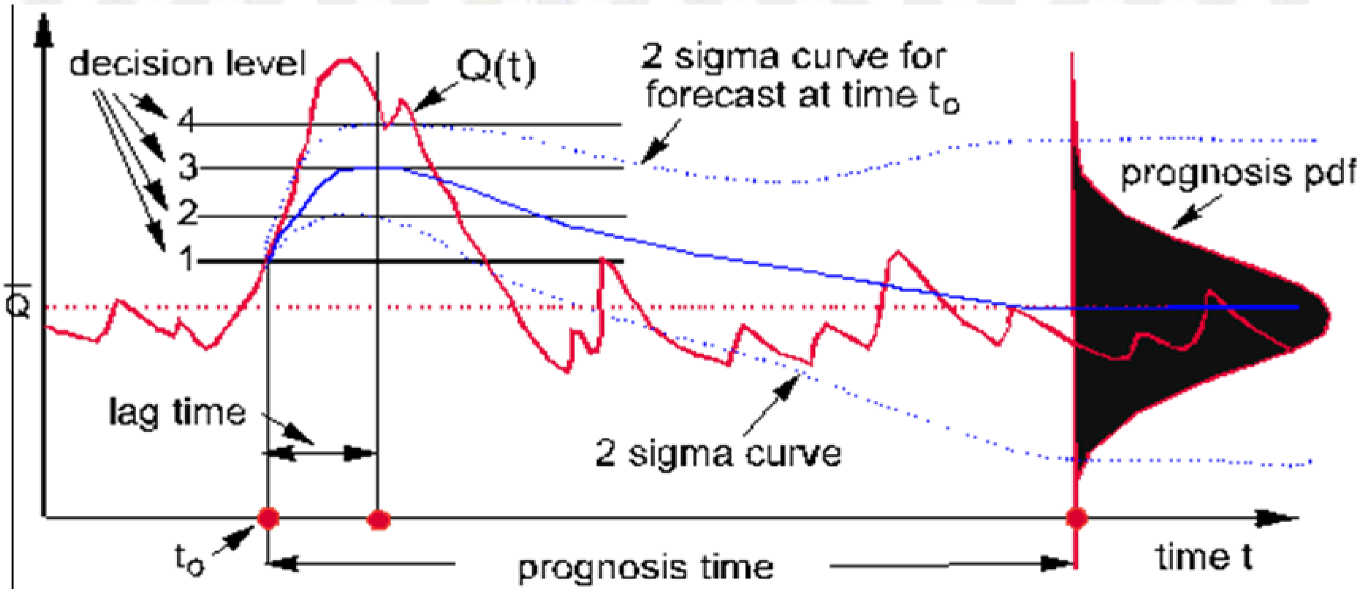

UNCERTAINTIES,
IN FLOOD FORECASTING SYSTEMS MODELLING

Flood forecasting is an important component of flood warning, where the distinction between the two is that the outcome of flood forecasting is a set of forecast time-profiles of channel flows or river levels at various locations, while "**flood warning**" is the task of making use of these forecasts to tell decisions on warnings of floods.

Author

Farhad Daliri , *Dam Consultant & Hydrologist*

Revised 2, 2020

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Knowledge is empty of limit,

so we have not enough time to learn every thing if you want to deep it in the real world.
Farhad Daliri, 2015

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"I can foretell the way

of celestial bodies, but can say nothing of the movement of

a small drop of water"
Galileo Galilei centures ago

UNCERTAINTIES

IN FLOOD FORECASTING SYSTEMS MODELLING

By:

Farhad Daliri , Dam consultant & Hydrologist

Signature

UNCERTAINTIES,
Revised 2, 2020

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by Farhad Daliri in Persian, 2014, 2019.

Part I Primary Concepts

Chapter 2. Flood Forecasting Techniques

Chapter 3. Uncertainties in flood Forecasting systems

Chapter 4. Weather Forecasting

Part II Complementary Topics

Chapter 5. Uncertainty analysis in FFS

Chapter 1 Principle of FFWS design

Flooding from main rivers is caused by heavy rainfall upstream, or dam breach and can also be caused by flood surges up rivers from the sea – caused by high tides, low pressure and strong winds that all they can manage by FFWS techniques

1-1-Main measures to manage floods

Daliri, 2014, 2019 listed all flood control techniques [1], including mechanical and biological as well as systematic planning. Now In this text, 10 main measures that must be taken to prevent more flooding in the future:

1. Introduce better FFWS and flood alerts if must live with floods

At first, the governments must "improve our flood warning systems", giving people more time to take action during flooding, potentially saving lives, the deputy chief executive of the Environment Agency, David Rooke, said. Advance **flood forecasting** (FF) - **warning system** (WS) and pre-planning can significantly reduce the impact from flooding. Moreover**, Flood alerts** are issued by weather agencies to alert residents that flood conditions are a possibility. Flood Alerts are able to be used to warn those living in flood risk areas in addition to any press reporting.

Fig. 1-1 The floods are a national disaster in world

2. Modify our buildings to help them withstand floods

The focus should be on “flood resilience” rather than defence schemes, we can use concreting floors and replacing materials such as MDF and plasterboard with more robust alternatives. “We are going to have to live with flooding. “We need to be prepared and increase flood resilience:

- Waterproofing homes and businesses (Flood resistance)
- Moving electric sockets higher up the walls (increase resilience)
- ….. etc.

3. Flood defence schemes [2,9] and preparedness [3,4] and flood fighting

River flooding is often typified by long durations and relatively high velocities. We have a relatively good level of data to understand areas susceptible to river flooding, with studies of catchment areas, river profiles and flood plains helping the provision of effective river flood defences. Some river flood defence schemes utilise land upstream to store floodwater to regulate the flow through constrictions (retarding dams, by pass, flood spreading, artificial recharge etc.) – typically through towns and cities.

The other options for river and sea coastal defences are:

Permanent solid flood walls and banks. These have the benefit of being permanently installed, with minimal operation and maintenance cost. However, the visual amenity of rivers within an urban setting mean that these flood defence solutions can be obtrusive (Aesthetic sense), especially if above 1 metre in height. (kinds of Groyne, Epi, Gates).(Fig. 1-2).

Demountable river barriers. These river defence barriers normally comprise removable posts and beams that can be fitted along the side of a river in advance of a flood. There is no visual intrusion when not installed, but they do require a logistical operation to install and remove each time. (Fig. 1-3).

Glass Floodwalls. These have the benefit of offering permanent flood defence, whilst minimising the visual impact. Glass floodwalls can be incorporated with a solid wall to give greater heights of river flood protection, as well as with flood gates or demountable river defences. The Environment Agency’s recent 'Wells-Next-the-Sea' project illustrates the benefits of a glass floodwall over permanent and demountable defences.

4. Construct buildings above flood levels

We can construct all new buildings in flooding area one metre from the ground to prevent flood damage. Professor David Balmforth, who specialises in flood risk management, said conventional defences had to be supplemented with more innovative methods to lower the risk of future disasters.

Fig. 1-2 FLOOD GATES BY RIVERS

Flood gates help protect pathways and openings by rivers from flooding.

Fig. 1-3 For large scale flood defence, flood fighting and preparedness from river flooding, the Portable Cylinder Flood Barrier system provides a tried and tested alternative to sandbags.[2],[3],[4].

5. Tackle climate change

Climate change has contributed to a rise in extreme weather events, scientists believe. Earlier governments from 195 countries pledged to “pursue efforts” to limit the increase in global average temperatures to 1.5°C above pre-industrial levels. “It is now crucial that world leaders deliver on the promise of Paris,” Ms Bennett said. “The pressure is now on the British government to reverse its disastrous environmental policy-making.” Moreover we can estimate effect of storm and flood extreme values by uncertainty analysis.[1].

6. Protect wetlands and introduce plant trees strategically

The creation of more wetlands and agricultural and forest management – which can act as sponges, soaking up moisture – and wooded areas can slow down waters when rivers overflow. These areas are often destroyed to make room for agriculture and development. Halting deforestation and wetland drainage, reforesting upstream areas and restoring damaged wetlands could significantly reduce the impact of climate change on flooding, according to the conservation charity.

7. Restore rivers to their natural courses - river training & engineering

Many river channels have been historically straightened to improve navigability. Remeandering straightened rivers by introducing their bends once more increases their length and can delay the flood flow and reduce the impact of the flooding downstream.

8. Introduce water storage areas

Following the severe flooding of 2009 a £5.6 million flood alleviation scheme was established in Thacka Beck, on the outskirts of Penrith, Cumbria. More than 675 metres of culverts underneath the streets of Penrith were replaced and a 76,000m³ flood storage reservoir – the equivalent of 30 Olympic sized swimming pools – was constructed upstream to hold back flood water. The risk of flooding from the beck was reduced from a 20 percent chance in any given year to a one percent chance, according to Cumbria Wildlife Trust.

9. Put up more flood barriers

The Environment Agency uses a range of temporary or “demountable” defences in at-risk areas. These can be removed completely when waters recede. Temporary barriers can also be added to permanent flood defences, such as raised embankments, increasing the level of protection.

“As the threat and frequency of flood risk increases, the use of passive flood defence (Deploy-Auto) or Infrastructure Intelligence has to be the only realistic long term solution. Mr Kelly’s company was responsible for designing a self-activating flood barrier he said had proved to be “invaluable” in protecting properties close to the River Cocker.(Fig.1-4)

Fig. 1-4 Passive flood defence- Infrastructure Intelligence

10. Watershed management based on Systematic planning of soil-water-plant-human

Inappropriate soil management, machinery and animal hooves can cause soil to become compacted so that instead of absorbing moisture, holding it and slowly letting it go, water runs off it immediately. Well drained soil can absorb huge quantities of rainwater, preventing it from running into rivers.

River basin is work unit for water management. Watershed or catchment or river basin management include all above mention together. Daliri (2009) showed, river basin management based on concept of hydro-system engineering can be solved by LP programming in Lingo software [5, 6]. He mentioned softwork structures (by pass, dyke, chek-dam, gabion, …ect.) and hardwork structutres (Big dams, .. ect.) as well as biological methods (pitting, reforestation,… etc.) beside environmental and economic considerations can be set in LP or another integrated water and system planning.

1-2-Terminology of FFWS

Flood definition

In this book, flood is damaging flood. In coastal sea floods such as tsunami, flood is rising tide that can be a huge water body with high speed toward the coast. In river floods, flood is rising in discharge or water level over areas that are not normally submerged [1].

River-Flood forecasting (**RFF**) is the use of forecasted precipitation and streamflow data in rainfall-runoff and streamflow routing models to forecast flow rates and water levels for periods ranging from a few hours to days ahead, depending on the size of the watershed or river basin[1]. Flood forecasting can also make use of forecasts of precipitation in an attempt to extend the **lead-time** available.

A Flood warning system (WS) is closely linked to the task of flood forecasting. The distinction between the two is that the outcome of flood forecasting is a set of forecast time-profiles of channel flows or river levels at various locations, while "flood warning" is the task of making use of these forecasts to make decisions about whether warnings of floods should be issued to the general public or whether previous warnings should be rescinded or retracted.

Real-time flood forecasting at regional area can be done within seconds by using the technology of artificial neural network.[1] Effective real-time flood forecasting models could be useful for **early warning** and disaster prevention.

Types of flood alerts

In the United States, a **flash flood watch** is issued by the National Weather Service (NWS) when weather conditions are favorable for very heavy rain that could cause flooding or flash flooding. A watch (**Yellow Situation**) does not mean that flooding is occurring, only that weather conditions have created or will create a significant risk for it. If flooding occurs, a flood warning (**Red Situation**) or flash flood warning would be issued and immediate action should be taken. A flood warning or flash flood warning is issued when flooding is imminent or already occurring. When flood warnings are issued, it means that area waterways will likely soon be in flood. Not all flood watches suggest that large-scale flooding, such as during landfalling tropical cyclones, is possible.

Flash flood watch is issued by the National Weather Service when conditions are favorable for flash flooding in flood-prone areas, usually when grounds are already saturated from recent rains, or when upcoming rains will have the potential to cause a flash flood. Also, when time of concentration is very short, the basin potential can cause flashy flood [1]. These watches are also occasionally issued when a **dam may break** in the near future.

PDS watches (Particularly dangerous situation)

In the event that a flash flood watch is likely to lead to a major flash flood disaster, enhanced wording with the words This is a particularly dangerous situation (PDS) can be added to the watch; this is occasionally issued.

Flood alerts in other countries: (National Flood Warning Services)

The type of flood warning service available varies greatly from country to country, and a location may receive warnings from more than one service. Countries such as **Australia** also issue similarly worded warnings. In **Canada**, a **heavy rainfall warning**, which indicates rainfall amounts that could produce flooding are expected, has basically the same meaning as a flood watch.

In **Australia**, the Bureau of Meteorology issues a flood watch that covers similar conditions to Flood Watches in the United States. However, they are known by slightly different names in some areas. In Europe, there is the European Flood Alert System.

In **Iran**, Daliri.F categorizes flood alert similar **coloring maps** based on real time flood zoning and concept of above mentaions.

In the **United States**, the National Weather Service issues flood watches and warnings for large-scale, gradual river flooding. Watches are issued when flooding is possible or expected within 12–48 hours, and warnings are issued when flooding over a large area or river flooding is imminent or occurring. Alerts can be issued on a county-by-county basis or for specific rivers or points along a river. When rapid flooding from heavy rain or a dam failure is expected, flash flood watches and warnings are issued.

In the **U.S. and Canada**, dissemination of flood warnings is covered by Specific Area Message Encoding (SAME) code FLW, which is used by the U.S. Emergency Alert System and Radio-network and in Canada's Weatheradio Canada network.

"**Flood statements**" are issued by the National Weather Service to inform the public of flooding along major streams in which there is not a serious threat to life or property. They may also follow a flood warning to give later information.

The Iowa Flood Center at the University of Iowa operates the largest **real-time flood monitoring system** of its kind in the world. It includes more than 200 real-time stream stage sensors that feed data into the Iowa Flood Information System where data can be viewed, online, by disaster management staff and the general public. The stream stage sensors, mounted on bridges and culverts, use ultrasonic sensors to monitor stream and river levels.

Other alerts:

Tornado warning, Tornado watch, Severe thunderstorm warning and watch.

1-3- Framework of FFWS

The twelfth session of the Commission for Hydrology, held in Geneva in October 2004, established flood forecasting and prediction as one of the thematic panel areas. Figure 1.5 shows the significance of flooding in the context of all water-based natural disasters [10].

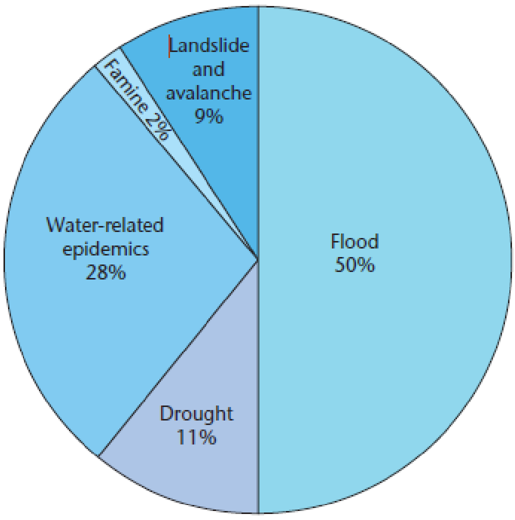

Fig. 1-5 Water related natural hazards, 1990-2001 [10]

Extreme weather events over the last decade have fueled the perception that, whether due to anthropogenic global warming, and other human interference, flooding is becoming more extreme, more widespread and more frequent. “As the risks and the costs of such natural disasters are likely to increase due to global social and environmental changes, there is widespread debate among stakeholders and activists “on issues of responsibility and liability, as well as on the appropriate measures for mitigating losses and providing relief to victims” (Linnerooth-Bayer and Amendola, 2003, [10])”. Such prospective developments have given rise to increased emphasis on the improvement of operational flood forecasting and the enhancement and refinement of flood-risk management systems (Arduino et al., 2005, [10]).

Essential elements require to organize an effective real-time Riverine Flood Forecasting Systems (RFFS) or other FFS are:

-Weather-prediction (quantity and timing) based on numerical models or other technology

-Hydrometric stations (manual or automatic) linked to telemetry

-Flood forecasting models linked to the observing network

1-3-1-Main components

We can count, main components of a FFWS the following or figure 1.6:

- Basic data of meteorology, numerical weather prediction such as GCM, hydrology, hydraulic and function of system (physiography, infiltration, relief, land use, vegetation…), based on expected accuracy in historical and real-time data for prediction of flood characteristics (severity, time of onset, extent and magnitude of flooding);
- Integrated system models (Mike, etc.) to Preparation of forecasting information for riverine flood or coastal sea surge and level forecasting;
- Warning systems (linked to Telemetry, models, ..) and warning messages or other communication tools, giving clear statements and Interpretation on what is happening, forecasts of what may happen and expected impact;
- Have a plan during warning for goal points, Communication and dissemination of such messages, which can also include what action should be taken;

- Symphonic of organization structure: Response to the warnings by the agencies and communities involved;
- Improvements and develop this process after events;
- The linkages Hydro-Informatics tools and other technologies such as IT, GIS, RADAR, Satellite, etc;

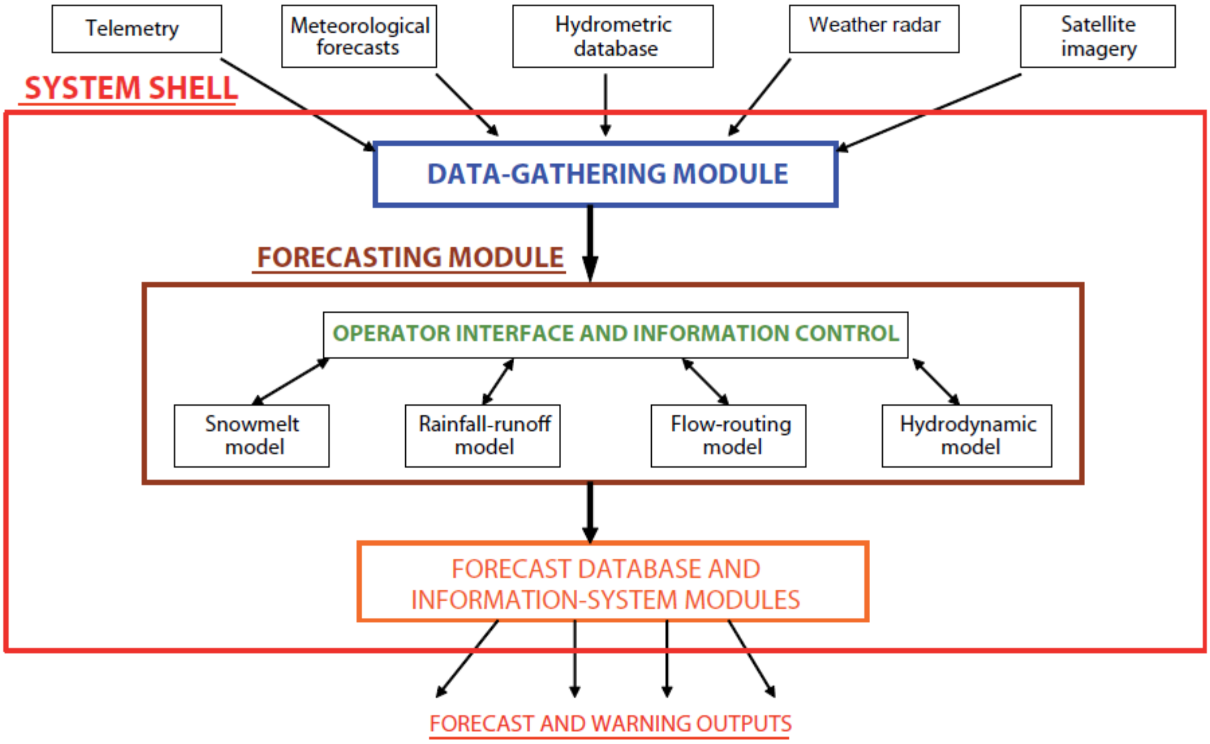

Fig. 1-6 Main components of a FFWS, WMO-2011 [after Wallingford Software]

1-3-2 Institutional aspects

In Iran, Flood management requires a cooperation and variable degree of response from the regional and local water management, municipal authorities, transport and communications operations and emergency services in home office. So the institutional structure and responsibility may become complicated for operative FFWS. A flood forecasting and warning system needs to have clearly defined roles and responsibilities. “These are wide ranging, covering, inter alia, data collection, formulation and dissemination, uncertainty of outputs and any legal or liability requirements”[10].

In Iran, Several ministries carry separate responsibilities for activities related to flood forecasting and warning. If activities of flood forecasting and warning be focused in the hydrometeorological sector is a relatively better. This situation provide the opportunity to enhance the development of monitoring networks specifically for flood forecasting and warning purposes for instant. Hydrological networks comprise instruments that have electronic facilities for data storage and transmission (raingauges and water level recorders) and meteorological networks can focus on collection and delivery of satellite and radar data.

1-3-3 Legal aspects

In many countries governments can provide assistance in rebuilding after floods, but there is no legal obligation. Insurance is increasingly fulfilling the role of government in recovery actions. Liability in strict legal terms is difficult to apply to the various activities in flood forecasting and warning. Any flood forecasting and warning system has to deal with uncertainty. This situation also leads to insurance companies deciding on what is or is not a worthwhile risk, which often leads to properties in high-flood-risk areas being uninsurable[10].

1-4 Main considerations of FFWS

Flood control is very expensive and there are many environmental, technical and economic limitation for flood control structures. Moreover design an adequate flood forecasting and warning services for protection of lives, assets and support of the civil protection and emergency response services in these areas is a growing necessity in many countries. The type and level of these services that is required or can be achieved technically and economically. In the following subsections Main considerations of FFWS will be examined:

1-4-1 Technical considerations

1-4-1-1 Watershed types

The most important parameters of catchment that can be effect on flood characteristics such as flood wave velocity and travel time are river slope, reach length and steepness, slope of basin, basin size, density of channels, and shape of basin. These parameters can measure in physiography study by GIS tools and some field sampling in supplementary studies.

In urban area and catchments that man-made structures exist also other parameters such as pipe lines, dam reservoirs, kinds of flood wall, channels, culverts, bridges, high proportion of effective pavement area, etc. must be study. Moreover, types of catchment can be characterized based on basin area and their different temporal and spatial responses to hydro-meteorological pulses:

A) Basin size of urban area are very small (less than 5 or 10 km^2), with densely populated and impermeable surfaces so the system respond in the order of one or two hours and can overwhelm the capacity of the drainage network. Urban basins may be have several inputs from Mountain Rivers in upstream.
B) Small sized of catchment areas are set between 10 to about 50 or 100 km^2 which will often produce rapid run-off specially with steep slopes that can be take travel time about few hours with react quickly. This situation often there is in up-stream of the big watersheds.
C) Medium sized of Watershed areas of between 100 to 1000 km2 characterized by long-distance flow propagation with varying contribution of tributaries. For these basins, flood can take half a day to affect the lower reaches. Also response of the systems in this range area and upper than, relevant to slope and structure of the soil specially.
D) Large sized of rivers have the basin areas of between 1000 to 10 000 km^2. For these basins, flood can take days to affect the lower reaches.
E) “Basins and continental rivers with catchments in excess of 10 000 square kilometres form a subset of large rivers for which flood response is in terms of weeks and reflects major seasonal meteorological conditions” [10].
F) Other kinds of flooding such as groundwater flooding, Groundwater-controlled river systems and interface flooding in estuaries (combined or single influence of tide effects, maritime storm surge, riverine floods, and wind effect in wide estuaries) there are. All of them have specific systems (f (.)). Propagation lead time in estuaries is of order of several hours depending on the length of the upstream reach, or wind intensity over estuary and in Groundwater-flooding systems can produce long-duration flooding, lasting several weeks in some cases.

1-4-1-2 System responses

If in a linear simple system, Y is input, and f (.) is function, so response R of the system is [1]:

$$R = f(.)\,Y$$

Understanding function of the system and other coefficients and parameters in above equation, before design an effective FFWS is necessary [1]. R is flood response, and it depends to f (.) in here flooding processes or physical processes. “The nature of any forecasting services that may be provided is firstly dependent above all on the types of flooding processes occurring in the basin” [10]. So it is clear that any one forecasting service may need to accommodate a range of basin types or f (.). (Table 1-1).
In forecasting services that based on meteorological data only, or combine of it with hydrological data (effect of f (.)) we can have other understanding of type of services.

Table 1-1 Interaction between basin size, physical process and flood response [10]

Type of basin	*Physical process*						
	Wind	*Infiltration*	*Rainfall intensity*	*Runoff*	*Propagation*	*Tide and surge*	*Water table*
Urban		X	XXX	XXX	X		
Upper basin		XX	XX	XXX	X		
Long river	X		X	XX	XXX		X
Estuary	XXX				XX	XXX	
Aquifer	X			X		X	XXX

XXX: dominant effect XX : direct effect X: minor effect

Based on the above mentioned in urban area a critical rainfall threshold may be benefit in FFWS design (pluvial flooding) and for the identification of flooding hot-spots in low lying parts of towns or where drainage systems there are not. So at first must understand the f (.) system then design FFW services based on combination of real conditions. It is clear can be monitored and prediction of system behaviour by a combination of observation and modeling based on different approaches of each type of basin flooding (physical processes). For example, in the urban area or basins with react quickly, to predict assuring sufficient lead time, emphasis must be on effective real-time meteorological observations and forecasts, rapid transmission and processing of data as well as understanding of the bahaviour of localized high intensity storm characteristics and the capacity of drainage systems. In this situation the good quality meteorological forecasts may be used to produce early, modelled flood estimates.
In large basin areas emphasis is on the distribution and patterns [11, 12] of rainfall as well as the observation of hydrological responses of contributing basins. Although in some cases, local storm data observations by telemetric raingauges or radar is important (localized flood response).

1-4-1-3 Flood types

Before design a FFWS we must have a basic studies on historical flood hydrology of the region. For example cause of flood in an area may be relevant to dam break probability or seasonal storms or intense local storms. In tsunami disaster for example, cause may be relevant to gravity of the moon (tide), wind, earthquake, landslide in sea or air pressure. So methods of forecasting and warning are different based on source and conditions of flood event such as urban floods, fluvial (riverine) floods, man-made floods, groundwater flooding, single and multiple event floods, flash floods, seasonal floods, coastal floods, estuarine floods, snowmelt floods, ice or debris-jam floods. There is thus no set design for a flood forecasting system and each will require a different forecasting approach. Thus headwater areas may require a system concentrating on flash floods, whereas flood plain areas may need a system to be focused on the slow build-up of flooding and inundation. [1,10].

Flash floods

Flash flooding are often the result of heavy rains with short duration such as intense and short duration convection storms often in summer, or frequent severe thunderstorms over small basins with steep slopes. “This type of flooding commonly washes away houses, roads and bridges over streams reach and so has a critical impact on communities and transport in these often remote areas. Moreover, Flash flooding can also occur in localized areas when ground has been baked hard by a long, dry period” [10].

Riverine floods (fluvial floods)

These floods can occur as a result from wet or dry conditions in an upper portion of a catchment of major seasonal rainfall activity based on **monsoon conditions** in basin-wide situation that can last for periods of several weeks. In these conditions, a number of individual peak or multiple event floods can occur. Also this type of flooding with heavy rains lasting several hours to a few days over a drainage basin may be are associated with **cyclonic disturbances**, **mid-latitude depressions** and **jet-stream** storms (Iran, Flooding, March-2019), with well-marked synoptic scale frontal systems, single or successive weather disturbances following closely after each other. All above mentions are dangerous to human life as well as flash floods are riverine flooding that such as spilling over the natural banks or artificial embankments (**man-made floods**) over flood plains as a result of flow exceeding the capacity of the stream channels can forecast and warn when occur over a wide range of river and urban or rural catchment systems.

Snowmelt floods

We must study and analyzing synchronization of snow melting with temperature rapid rise and warm, heavy rainfall.

This situation can occur in upland and high latitude regions with huge snow pack over winter, where the spring thaw produces meltwater run-off. If the sub-soil remains frozen or/and there is a hardpan layer in 1 to 3 meter depth from the top-soil, flood disaster can be further exacerbated.

Urban floods (pluvial floods)
Urban drainage systems include pipes, culvert, prismatic channels, river channels, culvert, manhole and wastewater network, pumps, ect. Run-off creates from paved and built areas within towns and cities and up-stream river basins. Urban flooding occurs when the drainage system is weak (there is an intense storm bigger than design return period) or lack of maintenance, especially in down-stream (In low-lying areas formation of ponds due to drainage obstructions caused by debris blocking drainage culverts and outlets).

Coastal floods
In this kind of the flood, such as tsunamis, raising of sea levels may be due to low atmospheric pressure, gravity of the moon (tide), high winds, earthquake, and landslide in sea or combination of 2 of them. Number of major cities situated in delta areas or major estuaries or confined sea areas, piling up of water is amplified by a combination of the shallowing of the seabed and retarding of return flow (cyclones) or winter depressions [10]. If river floods empty to sea, in joint place or inlet areas, (**Estuarine floods**) body of the flood water will be obstructed due to the sea surge or vice versa. In this situation, back-water can be miserable to reach stream to several kilometers in up-stream (interaction between the seaward flow of river water and landward flow of saline water). Although this kind of the floods are frequently and less severe than flooding caused by storm surges, mostly experienced in deltaic areas of rivers along the coasts.

Other natural floods
Similar dam break flood (man-made floods) there are 2 other kinds of natural floods that named ice and debris-jam floods. If water accumulate behind of the ice floes or landslip, when theses collapse or are breached, severe flooding can result. Although Prediction both of these are very difficult, we can predict hazardous zones.

1-4-1-4 Meteorological considerations

Climatology and meteorology observations and forecasting are a vital requirement especially in small-sized basins. Meteorological phenomena are the prime natural causes of flooding, either as rainfall, snow or snowmelt. So it is important that a representative proportion of the raingauge network (time and space) is linked to the forecasting and warning control centre by telemetry. This has a three-fold aim:

(a) To monitor the system;
(b) To give warnings against indicator;
(c) To provide inputs for rainfall–runoff models.
These events may be:
- Seasonality of rain-bearing Systems: (for example Monsoon Asia, tropical Africa and Central America). For this area must to be paid to ensuring sufficient staff cover to allow both regular situation updates and round-the-clock monitoring of severe conditions.
- Random occurrence: That staff routine tasks may be wider.

Weather forecasting may be based on:

A) Climatology understanding:
   - The understanding of rainbearing systems, their seasonality and the extremes of their behavior;
   - Understanding the types of weather systems from which flooding can originate will contribute largely to decisions about what sort of observational and forecast systems may be required; The most effective means for rapid recognition (flash floods) of an event would be by satellite or radar, while broad scale, synoptic forecasting would be of limited value.
   - Hydrometeorological statistics dealt with from climatology data: (primarily rainfall, but also evaporation). The purpose of the data and statistics is to estimate the severity and probability of actual or predicted events and to place them in context.
   - Historical data: (evaporation and/or climatological stations)

B) Synoptic & Climatology understanding: forecast methods based upon analysis of a set and/or series of synoptic charts or/and maps; the most common means of arriving at a weather forecast.

1-4-1-5 Hydrological considerations

Having real-time information and an understanding of the overall flood characteristics of the area is necessary. Water levels in rivers, lakes, river discharge, velocity of the floods and in some cases groundwater levels are the most important key observation and real-time-data requirements of the hydrology. The observation stations provide basic data for historical analysis and telemetry measuring to provide data to a control center of FFWS. In general, main means to predict of levels, timing and extent of flooding are:

- Simple methods:

These methods include as tables or graphs of level-to-level correlations (upstream-downstream relationship between water levels or ect.) and time of travel (the time taken from a peak at an upstream point to reach a lower one). Water level ranges at given points (flood-risk site) can be linked to various extents of flooding (flood zones), so a series of thresholds can be set up to series of watching and warning through telemetry.

- Comprehensive methods:

Real-time flood modelling specially based on IFM or Integrated Flood Managements, in crisis management cycle (preparedness, response and recovery) [1]) can provide the facility to provide more comprehensive information on predictions of flood characteristics such as levels, timing and extent of flooding and flood mitigation measures.

1-4-1-6 Risk, Uncertainty and impacts

A wide discussion about flood risk and uncertainty in water resources can be find in refer [1]. Briefly risks relevant to uncertainties. In hydrology there are kinds of uncertainties such as: intrinsic and model uncertainties (Objective-first order). Intrinsic uncertainties can be estimate by reliability of analysis, return period based on economic losses. Model uncertainties include truncation, rounding, and parameter uncertainty. In FFWS, other kinds such as society (population growth and density) and economic risks can be account also. FFWS has to operate over a range of event magnitudes (impacts) include small-impact flooding which can be manage by simple measures, such as installing temporary defences, closing flood gates and barriers (above mentioned), to larger scale flooding, where damaging floods and losses occur, and evacuation of areas at risk takes place or catastrophic events, for instant dam or embankment failure, that can be manage by FFWS with emergency action plans (EAPs), although my not be fully effective.

1-4-1-7 Service type

Selection level of the service relevant to costs, accuracy, data and the f (.), data requirements (such as inundation depth or extent or both of them, etc.), knowledge of the flood modeling, Operation and Maintenance and Repair condition (economic conditions) and severity of flood losses. The different types of services, from the simple levels to those of greatest quality, be summarized as follows by the author:

a) Threshold- based rainfall alert
b) Threshold-based flood alert
c) Flood forecasting with simple warning system

d) Flood forecasting with advanced warning system
e) Inundation FFWS

Threshold based rainfall or flood alert for simple services (basic minimal levels) can be based on real-time data measurements at synoptic stations or along rivers data such as flood hydrograph (lemingraph data recorder). Extrapolations and qualitative estimations are made at time intervals to revise the projection of potential or actual flood conditions. Knowledge of the behaviour of the river is requirement in a and b levels also. C and d levels that are more definitive Service types, based on the use of simulation tools and modelling (simple to sophisticated models). Simple methods such as statistical curves, level-to-level correlations or time-of-travel relationships to numerical models that integrate and replicate the behaviour of rivers throughout the basin, must be calibrated beforehand by using historical and future (regular checking) data from recorded floods [1]. The information delivered by a simple warning service as in the flood alert (sms, radio, siren, ect.) is set to station locations, and focused on specified locations at risk. In advanced warning systems (Vigilance mapping) produced a map-based visualization (for example the vigilance map in France) as an Internet service. The levels of risk derived from observations or models are characterized by a colour code (in the French example, greepropn, yellow, orange, red) indicating the severity of the expected flood. In inundation forecasting, that is the most sophisticated level based on hydrological or hydrodynamic level-and-flow models (distributed models, [1]) with digital representation of the flood plain land surface. This class is appropriate to sensitive areas of flood plain, where flood extent is dictated by minor relief, such as urban areas with housing areas, power stations, road or rail bridges and such as.

1-4-1-8 lead time

Lead time is an opportunity for exposed people to move vulnerable properties to upper storeys or put sandbags [2] or other small barriers in appropriate place that may require from one to two hours or Protection of larger infrastructure, setting up of road diversions and movement of farm animals to a place of safety may require lead times of several hours or for evacuating populations at risk places in large rivers but major potential impact that may require lead time in the order of days. The following equation describes concept of lead time simply [1]:

$$L_t = (T_c + T_m) - T_{fw}$$

L_t: Lead time,

$T_c = T_e + T_w$: Hydrological lead time (catchment response) or Time of concentration (T_c), Time of catchment entry (T_e), and wave travel time at critical reach (T_w);

T_m: Rain-forecast lead time

T_{fw} Time delay (Computations_ validation, calibration, rain or/and flood Forecast, dissemination).

In flood mitigation programs, increasing T_c can do by watershed management (biological or/and hard-works methods such as retarding basin dams and etc.). In small basins and urban area, rain forecasting and/or telemetric rain-gauge data or radar rainfall technology can provide additional advance warning because increasing T_m. Moreover huge computers can help to compute rapidly, so T_{fw} be short. Usually threshold measure between normal floods and flash floods is 6 hours and rain forecasting is necessary for flashy flood forecasing. Additional information can be found on the following Websites:

– Australia: http://www.bom.gov.au/hydro/flood;
– United States of America: http://www.weather.gov.ahps;
– France: http://www.vigicrues.ecologie.gouv.fr;
– United Kingdom: http://www.environmentagency.gov.uk/homeandleisure/floods.

1-4-1-9 Dissemination and warning systems

Flood warnings are distinct from forecasts, as they are issued when an event is occurring, or is imminent. Warnings maybe issue based on meteorological warning (Fig. 1.7) or hydrological (flood) warning (Fig. 1.8). Flood warnings must be issued to a range of users, for various purposes. These purposes include [10]:

(a) To bring operational teams and emergency personnel to a state of readiness;
(b) To warn the public of the timing and location of the event;
(c) To warn as to the likely impacts on, for example, roads, dwellings and flood defence structures;
(d) To give individuals and organizations time to take preparatory action;
(e) In extreme cases, to give warning to prepare for evacuation and emergency procedures.

So flood warnings need to be understood quickly and clearly and so considerable attention has to be given to how technical information is conveyed to non-specialists from organizations, the public, the media and in some cases illiterate population groups.

Prior to issuing a flood warning, consideration is given to [10]:
The needs of communities to activate emergency response plans;
The nature of the catchment or coastline and the lead time that may be provided;
Meteorological observations and forecast information on rainfall and coastal water levels;
Hydrological observations and flood forecasts reference to thresholds of historic or forecast flood levels (Fig 1.9).

Dissemination of flood warnings has moved towards a service whereby those at risk can pre-register to receive warnings by phone, email or text message from an automatic system, Floodline. Both warnings and updates about current conditions can carry by local radio stations. For example, live updates are carried by the Environment Agency's website showing which locations have flood warnings in place and the severity of these warnings.

The task of providing warning for floods is divided into two parts:

- decisions to escalate or change the state of alertness internal to the flood warning service provider, where this may sometimes include partner organizations involved in emergency response;
- decisions to issue flood warnings to the general public.

The decisions made by someone responsible for initiating flood warnings must be influenced by a number of factors, which include:

- The reliability of the available forecasts and how this changes with lead-time;
- The amount of time that the public would need to respond effectively to a warning;
- The delay between a warning being initiated and it being received by the public;
- The need to avoid issuing warnings unnecessarily, because of the wasted efforts of those who respond and because a record of false alarms means that fewer would respond to future warnings;
- The need to avoid situations where a warning condition is rescinded only for the warning to be re-issued within a short time, again because of the wasted efforts of the general public and because such occurrences would bring the flood warning service into disrepute.

A computer system for flood warning will usually contain sub-systems for:

- flood forecasting;
- automatic alerting of internal staff;
- tracking of alert messages and acknowledgements received;
- diversion of messages to alternates where no acknowledgement received.

FFWS without an effective dissemination of forecasts and warnings, is not achieved. This has been helped by the growth in tele-communications, the computer, the IT revolution, and increased ownership and coverage of media, such as radio and television, sms, internet. Nevertheless it is doubtful whether Internet communication of flood warning information can be entirely effective. The elderly and poor members of the community may not have the necessary facilities at home and it may also be doubtful whether people will consult Websites when a dangerous situation is in place. It must also be remembered that these systems are dependent on telecommunications and power links that are themselves at risk of failure during flood events. Other general warning systems such as flood wardens and alarm sirens should not be abandoned without careful consideration of the consequences and emergency services (police, fire service, civil defence) must be involved in communicating flood warnings and rescue (Fig 1-10).

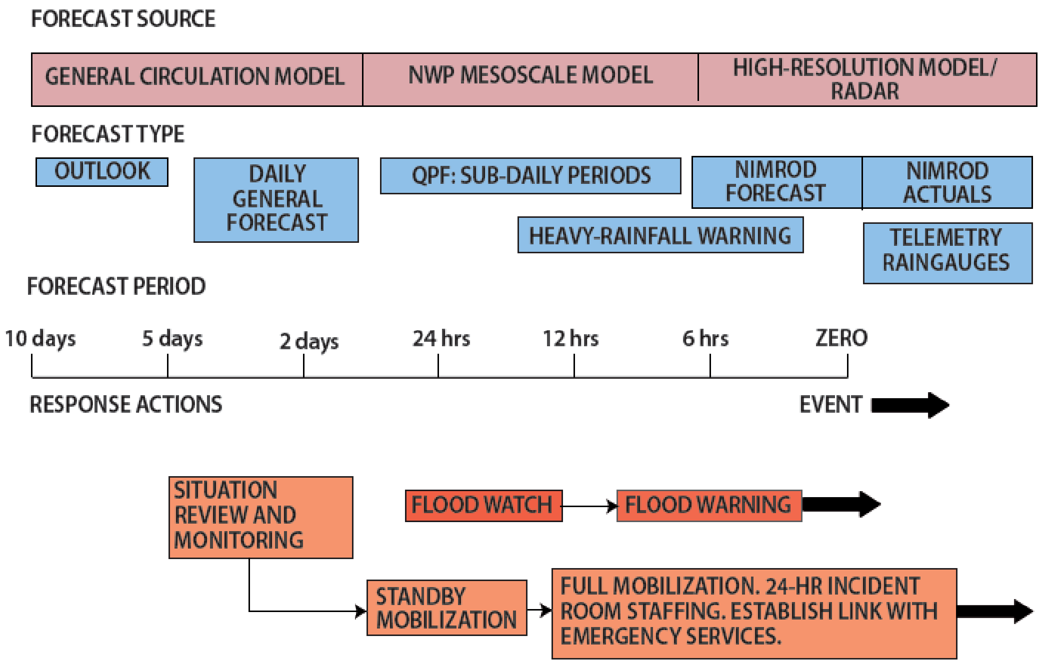

Fig. 1-7 forecasting lead time and warnings type based on meteorological warning [10]

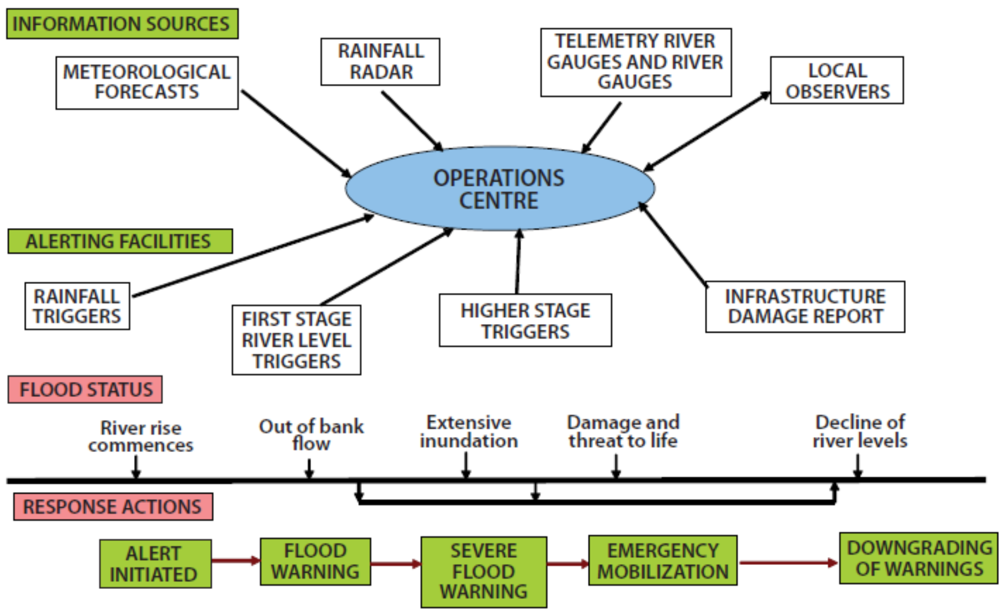

Fig. 1-8 Flood warnings and responses [10]

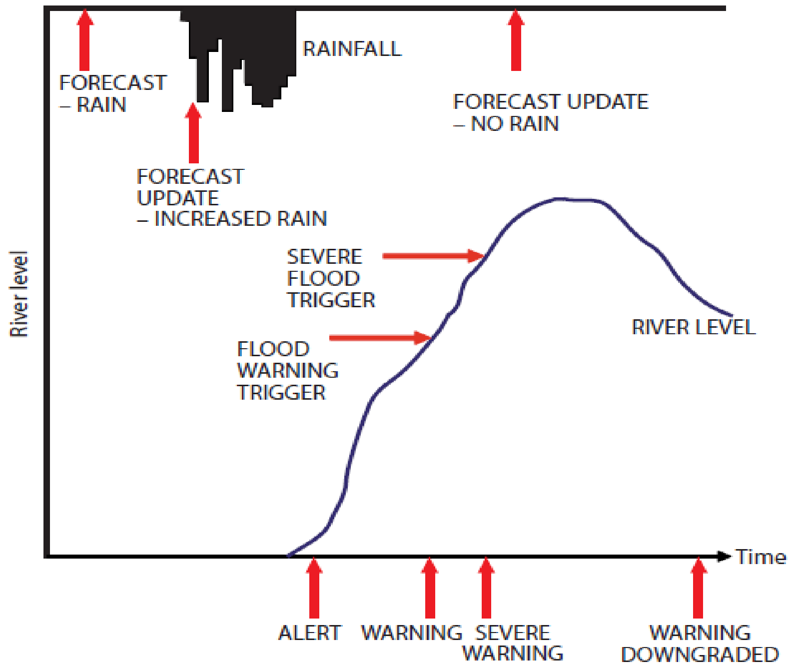

Fig. 1-9 Arrangement of trigger levels for various flood warning stages [10]

1-4-2 Data and technical requirements

Data requirements relevant to kind of FFS are variety and data rescue due to natural deterioration of the storing media always is vital. The overall data and technical requirements are summarized below:

- Meteorological data
- System function data
- Hydrological data

An effective FFS is integrated. So global data requirements without classification included:
-Real-time and past data_(spatial distribution): measurement of river flow and level, telemetric rain gauges network, ground based radars, satellites, airborne sensors, numerical weather prediction (NWP) models for quantitative precipitation forecast (QPFs) for example and ….(Full details of instruments and discussions about their location and siting can be found in the WMO guides referenced (WMO, 1983, 2007, 2008).).
-Discharge data or water levels and rating curves at appropriate gauged sections in rivers and from impoundments.

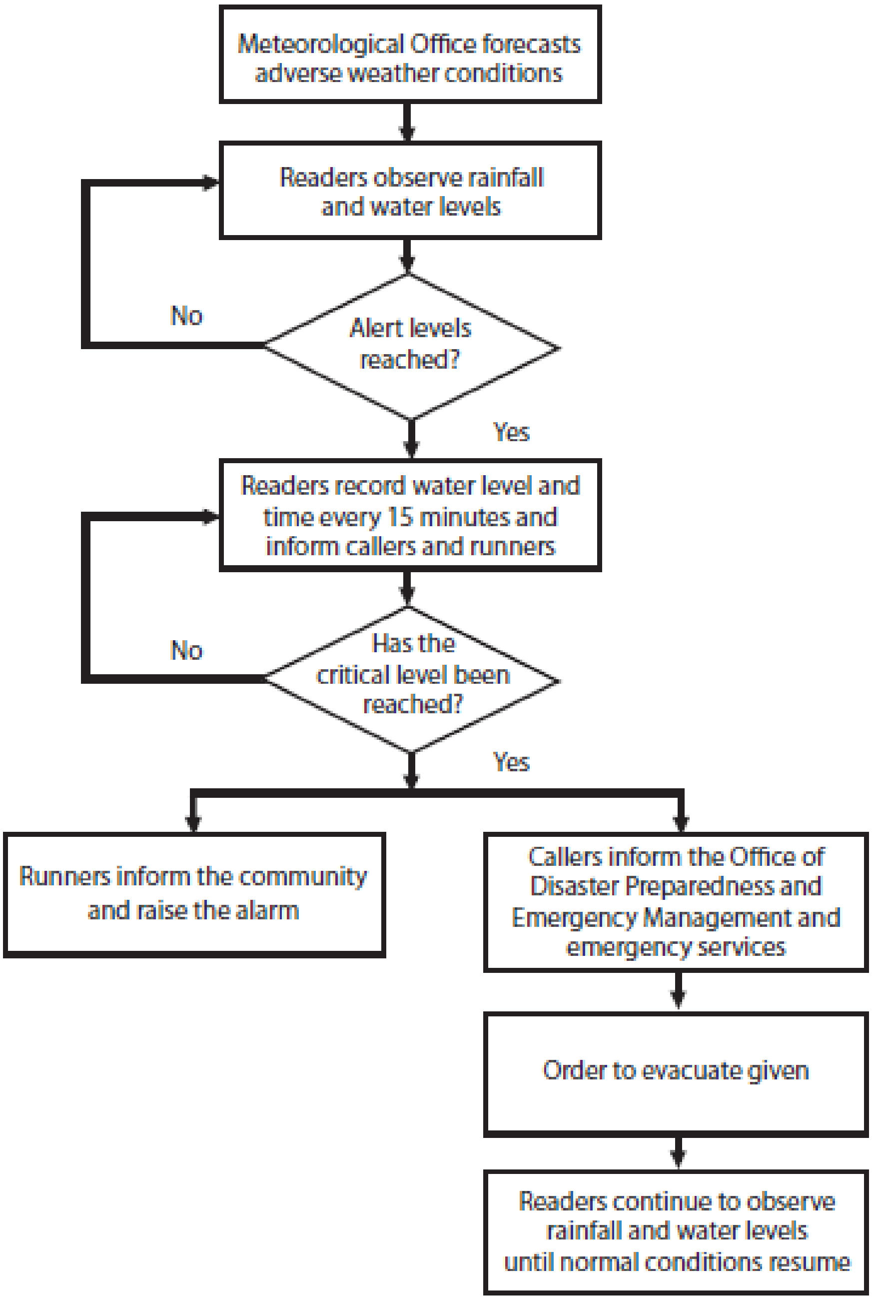

Fig. 1-10 Procedures for issuing flood warnings to rural communities in Jamaica [10]

- To produce realistic estimates of spatial flooding, Digital elevation model in risk area, and reach is necessary (topographic Information). Satellite sources are available to provide data globally at a horizontal resolution of 90 metres with a vertical resolution of ± 2 metres. This may not be sufficient for detailed modelling to provide an accurate indication of flood plain and channel capacity for hydraulic and distributed models. Data to a resolution of 20 metres horizontal and 0.5 metres vertical or better can be obtained from light detection and ranging (LIDAR) or side-looking airborne radar (SLAR) surveys (Veneziano, 2002).

-Soil moisture measurements, flood zoning, reach characteristic, geology, vegetation (land-use) data, population data at risk area, Inventories of properties at risk area, and ….

-Data for calibration during the required lead time of the flood forecasting model;

- A catchment and reach modelling to predict the effects of structures in river channel, reservoir operation, flood plain and flooded areas.

-Network of stream gauges (simple staff gauges to Doppler or ultrasonic sensing devices measuring level or flow or RLS …). The composition of the stream gauge network is determined by the requirements for lead time and accuracy (Check points) and also the locations where forecasts are needed (forecast points).

-forecast points: Forecast points are usually coincident with a stream gauge location, partly as a result of the modelling approach and partly to give operational verification (Check points). Forecast points can also be designated for a specific reach of a river where flood impact is potentially high, such as near properties, towns, or agricultural areas (Risk points).

-Rating curves: at a flow gauging station, an accurate rating curve (stage–discharge relationship) should be maintained. Flow gauges at forecast points should have telemetric links to the operational control centre.

- Although traditional techniques for rainfall forecasting are still widely used (cost-effective), there are two major benefits for using radar data: a finer spatial resolution of the data field, and better real-time data availability because the ability to predict approaching storms before they reach the goal area. Also radar has advantages where rain gauges are sparse and/or storms are localized. But, if storms are large in area, the gauges (many rain gauges) tend to produce more accurate measurements of rainfall than radar. Radar will still give a better indication of the spatial distribution that gained by classical methods such as Thiessen polygons or Kriging interpolation.

- Although QPFs have considerable uncertainty, to extend lead time significantly, Numerical climate-prediction models at the global model, (RCM) or limited-area climate models (LAM) may be utilized, where available, to provide rainfall forecasts as inputs into flood forecasting models if sufficient accuracy can be realized (Fig. 1-11 and 1-12).

- Other data such as location of key transport, power and water supply infrastructure, systematic post-flood damage assessments and …

- Above data such as high-resolution DEM data can be linked to a GIS to provide visualization of flood inundation extent and flood plain infrastructure.

To combine the information in useful format, and DSS to producing forecast details with guidance and map forecasts showing flood inundation in real time.

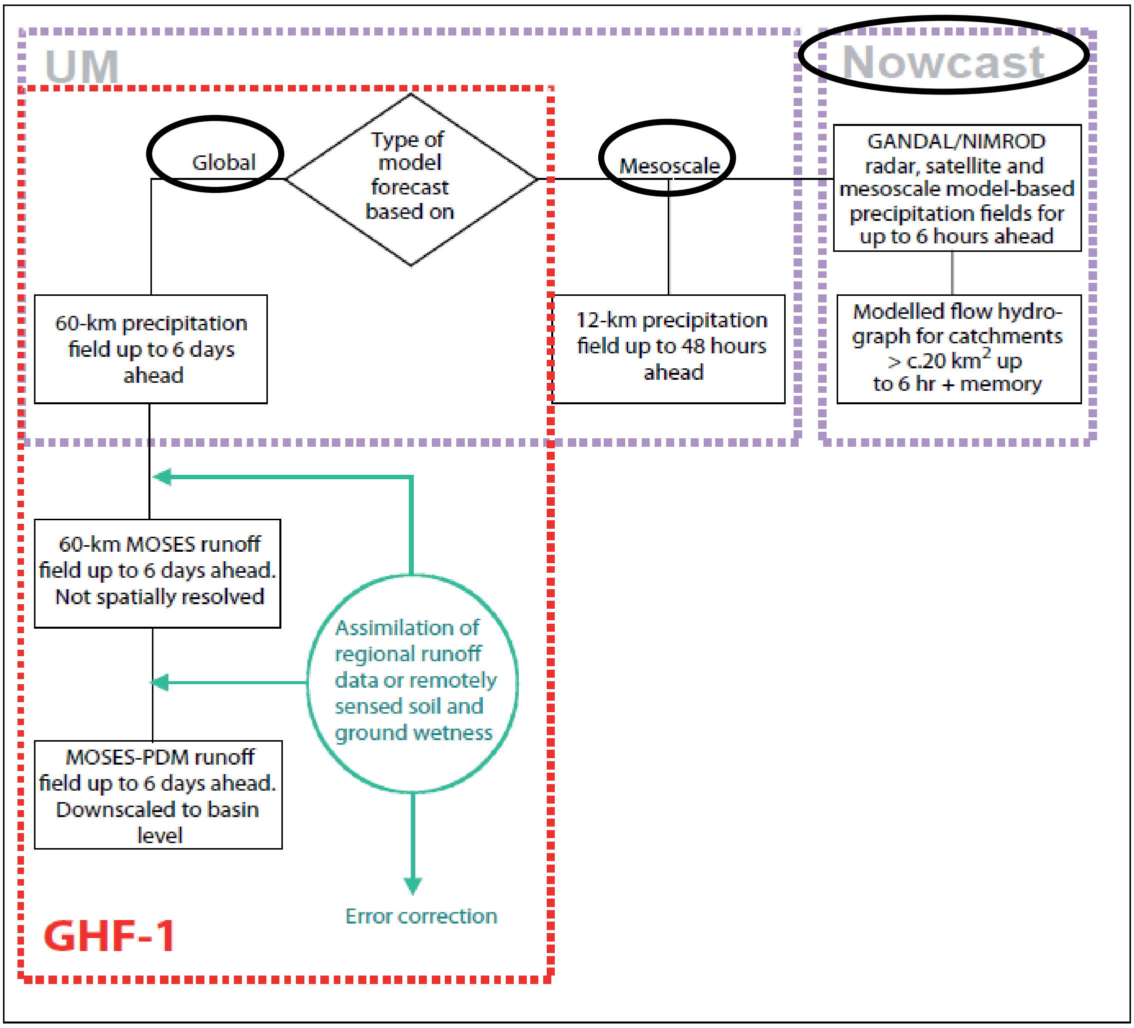

Fig. 1-11 Schematic for the first option of Global Hydrological Forecasts-GHF-1

1-4-3 Infrastructure

Before design the FFWS, which should initial be assessed is the capacity of the system for flood forecasting and to provide guidance on developing, based on the following topics:

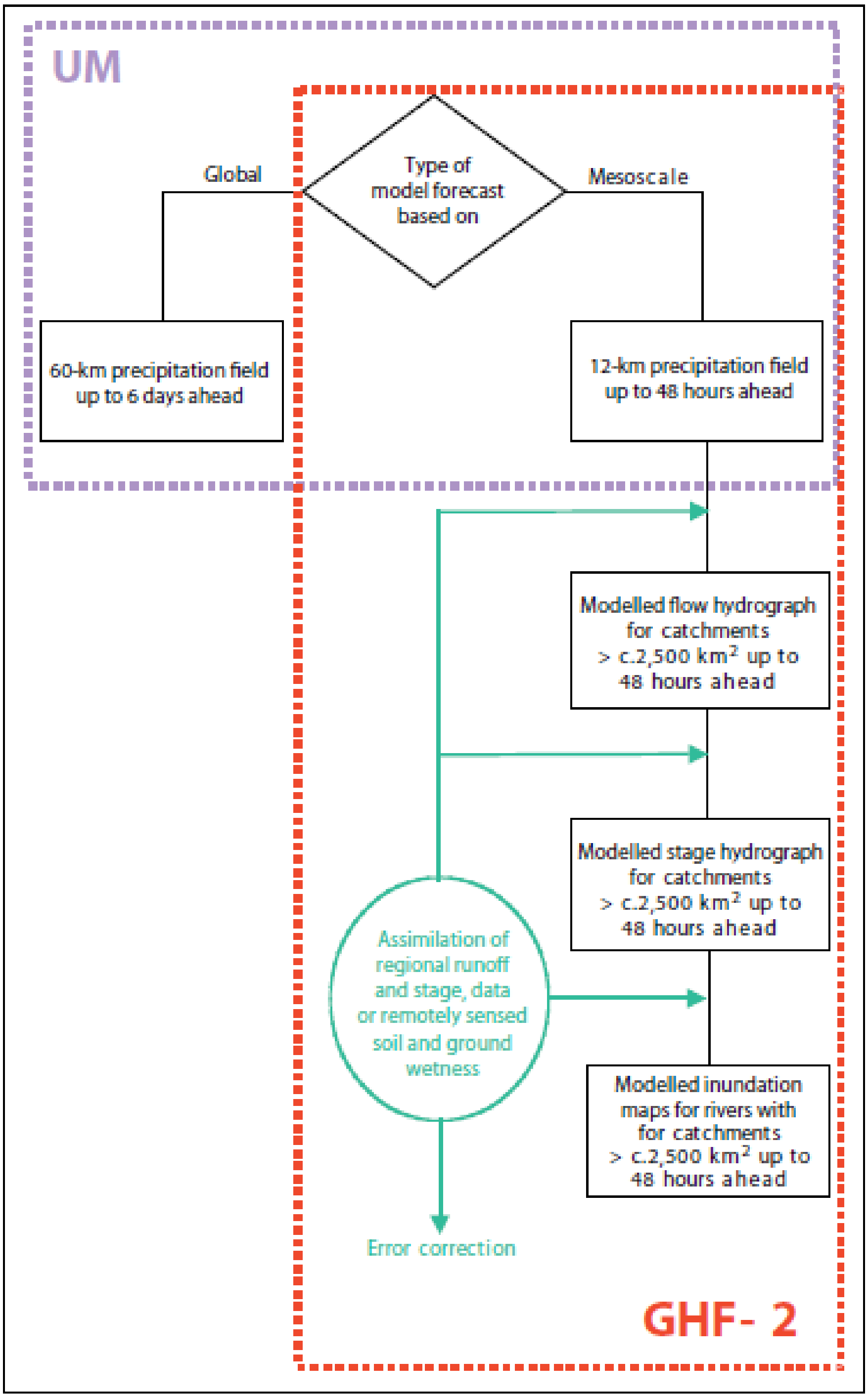

Fig. 1-12 GHF based on mesoscale model fields-GHF-2

-Technology of data gathering (What kind of information is available to the meteorological and hydrological services? Data sources will include the national observation networks, weather radar, up atmosphere stations and also access to international data, and weather satellite information. What is the status of the hydrometric network (rain gauges and water level detectors) that could be used in a forecasting system?

-Skills of flood forecasting staffs and modellers. Or what skills are necessary for the adequate development of a flood warning system?

-Methods and equipments of communication and warning system.

-What are the requirements of the end-users of flood warning information? [10].

-What are the arrangements for flood forecasting, and which government services are involved? Significant differences in the approach to meeting forecast needs occur when a single authority has responsibility (for example the meteorological service), or when it is divided between agencies (most often between the meteorological service and the river management agency) [10]. Or is the flood forecasting operation linked to surrounding countries, especially where shared river basins are concerned? [10].

Moreover, in general the basic physical requirements within which the service and its staff need to operate are:

- Buildings, alternative site for a backup operations centre and duty rosters belonging to their parent government department;

- Operations room with adequate space for desks, computer terminals and work-stations, data display facilities, and printing and copying equipment;

- Separate room should be provided for computers and telemetric equipment (air condition, controls to the entry of dust and dirt, operator safety,..);

- Direct line telephone, fax and Internet access for the head of operations;

- Briefing room with radio and television transmission facilities for contact with the media;

- Security arrangements consideration for duty staff;

- Equipment should be supplied with uninterruptible power supply (UPS) devices and standby generator facilities (automatically be set up and lighting to the units perhaps many hours);

- The flood forecasting and warning centre, should not be at risk of floods;

-Human resources: formal, adequate and suitably qualified staffing and experts and duty officers for such operations of flood forecasting and warning units and permanent flood-risk management (PFRM) is imperative. Also many of the temporarily assigned staff came from disciplines outside hydrology and river engineering;

-General requirements for staffing: There is no fixed optimum pattern to follow, but the following capacities must be available: Hydrological forecasters and modellers, meteorological forecasters, IT and operational technical communications specialists, communications with the media, public and Government, management and administration, research and development.

1-4-4 Operational concept

The concept of operations (system efficiency) is the defined interaction between the users, the forecast technology and the data. It defines how the operational forecast service will function to assure that users' requirements are met. There are many factors for this aim but the following factors should be mentioned [10]:

a) Forecast centre mission

There are many users (emergency services, civil defence, contingency managers, the media, agriculture, industry, hydropower organizations, water resource and flood control managers, water transportation and municipal water supply organizations) that have different requirements for forecasts and information that to be specified by individual arrangements and service agreements.

b) Communications

This comprises data receive and transmit tools which will include for example arrangement with telecommunications office and other authorities.

c) Operation of the data gathering network

In this case, concern is about all sources of data needed for forecasts, such as gauges, radar network and satellite downlink products to be received.

d) Forecast centre organization

Duty of the staff must be define, fore instant, how many technicians or professionals will staff the centre during routine and emergency operations. The educational and training requirements and the timing arrangements and deadlines for dissemination of staff need to be well defined. Also it is useful to maintain examples of all output products in the Operations Manual both for training purposes and for reference when queries from users arise.

1-5 Socio-Economic benefits of FFWS

Although these benefits of FFWS are very diverse, current knowledge about warning benefits is limited, indicating a need for further research especially as the benefits of flood warnings are likely to increase. Moreover the magnitude of benefits depends significantly upon the public's response to flood warnings in residential sectors as a warning response (sandbagging, evacuation,..) and efficiency of system in general (lead time especially). Most is known and capable of monetary estimation in the category of primary, tangible benefits (buildings, animals,…), particularly in the residential sector where data on warning response variables is accumulating [Dennis Parker, and et al, 2005].

Case study

"Planning for sandbagging as a response to flooding: a tool and case study"

This paper presents a simulation tool that allows local councils, emergency services organisations, and communities to explore the viability and details of sandbagging depots and their operation as one of the components in a preparation and response strategy to flooding. The tool was developed in collaboration with Victorian State Emergency Services and the City of Port Phillip Council. The focus of this case study is the coastal suburb of Elwood, which has a canal through its centre and a worrying increase in damaging flash floods. The tool that was developed is suitable for use in any location, once relevant geographical information and flood maps are supplied [2].

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/267639313

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Chapter 2 Flood Forecasting Techniques

Computer, Radar, GIS, Satellite, IT

For

the next generation of hydrological modellers in Flood Forecasting, F.Daliri, 2019

2-1- FF techniques classification

Daliri [2], listed all flood control techniques, including mechanical and biological as well as systematic planning such as planning flood risk management systems, flood forecasting and IFM_IWRM. Floods can be of many different types and scales and this drives differences in the architecture and implementation of flood forecasting systems [1]. Plate (2009) distinguished five different types of landscapes with characteristic flooding behaviour:

a) high mountain ranges, which are mainly subject to flash floods and geophysical flows,

b) foothill areas where floods are caused by intense rainfalls and snowmelt, and where inundation is widespread,

c) large floodplains where velocities are low and floods occur because the landscape is unable to quickly pass all the incoming flows,

d) urban areas where flooding is generated by inadequate sewer capacity and numerous barriers to flow, and

e) coastal areas where flooding is typically caused by cyclones and storm surges.

The mani components of an FFWS in riverian floods, (Fig. 1-6) include:

- Data collection (rainfall, water level, DTM, …)
- Data analysis (format, missing, trend, …)
- Data transmission
- Flood forecasting (river elevations, inundation extent, and time of occurrence for peak discharges with lead times), (Fig 2-1 and table 2-1).
- DSS and warning outputs dissemination to user

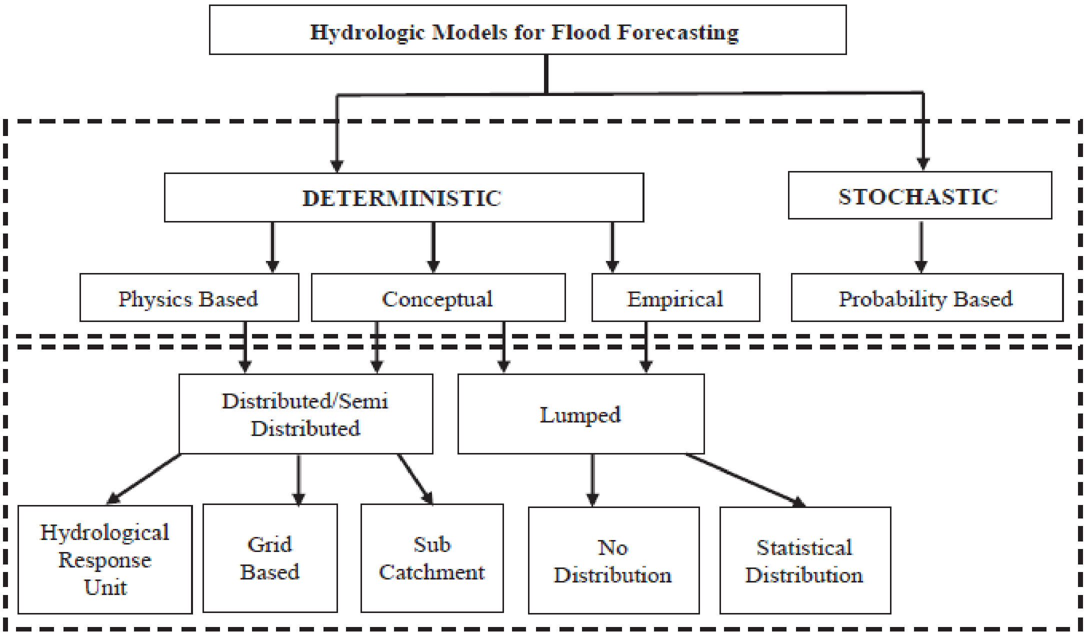


Fig. 2-1 Classification of methods used for Flood Forecasting based on model structure and type (WMO, 2011,[1])

Table 2-1 criteria for model classification

Criteria	Classification		
Spatial distribution	Lumped: black-box model	Semi-distributed model	Fully distributed model
Catchment modelling approach	Deterministic • Empirical • Conceptual ◦ Lumped ◦ Distributed • Physics based ◦ Grid based ◦ HRU based ◦ Sub-catchment based	Data Driven • Stochastic	Data driven • ANN • Fuzzy
Input data and basin scale	Stream routing models • Hydrological routing • Hydraulic routing	Catchment models	Combined catchment and routing models
Precipitation forecast	No precipitation forecast	Precipitation forecast	Radarnowcast
Updating	No updating	Updating model	Updating model

Also, According to the various concepts used in developing models, the models or methods maybe classified into five categories:

A) Based on correlation/coaxial diagrams between two variables or even more;

B) Mathematical equations developed using regression/multiple linear regression techniques which combines independent variable with one or more than one variable;

C)Hydrological models

c.1 Rainfall run-off model

i) Lumped

ii) Quasi-distributed

iii) Distributed

c.2 Routing techniques

i) Lumped, & Distributed;

D)Hydraulic models

d.1) Dynamic Wave routing;

E)Data driven hydrological models

i) Artificial Neural Networks

ii) Fuzzy expert system design for FF

iii) ANFIS (Adaptive Neuro-Fuzzy Inference System) models

Furthermore, models may be classified depending upon the way catchment processes are represented – deterministic, data driven and Ensemble models:

- Deterministic models

The process of transformation of rainfall into runoff in these models, is time dependent and is a function of the physical characteristics of catchment and rainfall. For example, deterministic rainfall-runoff (RR) models include components for the various hydrological and related processes, such as precipitation, infiltration and soil moisture dynamics, evapotranspiration, runoff generation and streamflow hydraulic or hydrologic routing. flow in natural channels or urban area during floods is typically unsteady, non-uniform, and includes interactions with tributaries and bifurcations with varying cross-sections and roughness, Groundwater seepage and sea coastal effects. Flood routing in such channels is most commonly accomplished by solving the full or simplified St. Venant equations to obtain flow depth and velocity as a function of space and time throughout the system [2]. 2D models are quickly becoming the standard of practice in many places (e.g. Jones et al. 2002), while 3D models are becoming increasingly applied in specific scenarios (e.g. Biscarini et al. 2010). However, the increased complexity of 2D and 3D models requires high-quality data and modelling expertise to produce accurate results [1].

- Data-driven models

Data-driven models are often referred to as black-box models, because they depend upon the statistical or cause–effect relationships between hydrologic variables without considering the physical processes that underlie the relationships (Luchetta and Manetti, 2003). Data-driven models can include stochastic models [7,8], (e.g. Regression models, Time- Series models, and Bayesian models) and nonlinear time series models (e.g. Artificial Neural Network models, Fuzzy Systems, and adaptive neural Fuzzy Inference Systems-ANFIS) that require extensive and high-quality time series of hydrologic data.

Practical applications of the data-driven models for flood forecasting are still lacking chiefly due to the two reasons: (i) data-driven models do not account for the changing dynamics in the physics of the basin over time (i.e. aggregation/ disaggregation/ changing land pattern); and (ii) the parameters of data-driven models are completely dependent on the range of the data (i.e. maximum and minimum) used for calibration. As a result, process-based hydrological models have traditionally dominated FF [1], [2].

- Ensemble forecasts

In ensemble or probabilistic prediction systems (EPS), a set of possible future states of the variable are provided through small changes in the initial conditions, different representations of the physical processes, and changes in parameterization schemes and solution schemes or using ensemble weather predictions (numerical weather predictions-NWP) as inputs (Thiemig et al. 2015). Rather than providing a single deterministic forecast, the EPS offers an ensemble prediction of hydrological variables, such as streamflow or river level, allowing the identification of the most likely scenario, that provide the added value to flood forecast for the issue of early flood alerts with more confidence. An EPS, in a way, consists of the propagation of uncertainties through the forecasting system. Notwithstanding the other uncertainties, prediction of rainfall is often the dominant source of uncertainty in FF. An example of operational ensemble FF systems is the European Flood Awareness System (EFAS) which makes use of multiple meteorological forecasts to produce probabilistic flood forecasts with estimates of uncertainty (Thielen et al. 2009).

Selection of a particular method or model (Table 2.2), and its accuracy for a given site is largely governed by data availability; knowledge of forecaster, forecasting objective, institutional capabilities, experience with the basin or system characteristics. Before selection of an appropriate method, at first modeler must design quality and quantity conceptual model of the system [2]. Details of the modeling process, described in text book of Water and environmental modeling (flood control-water supply-groundwater management) by auther, 2014 and 2019 (Fig 2-2). In following sections, some FF techniques described.

2-2- FF techniques

2-2-1-Correlation/Co-axial diagrams

2-2-1-1- Runoff from small watersheds

The coaxial correlation method [9] to predict runoff from small watersheds, is a multi-graphical Approach, and the physiographic, hydrologic, geographic, and geologic characteristics are considered. Using this method, however, these characteristics are combined into the variables under consideration and are evaluated and related from a statistical standpoint. Investigation of the results from the hydrologic viewpoint should substantiate the results if the method is valid. This formula should include the following parameters:

-Volume or height of precipitation, and duration,…

- antecedent_ precipitation index (API), basin recharge, …

-week of the year, …

The application of this technique (Fig.2-3), allows a graphical representation of the relationships between several variables, all of which influence some dependent variable of interest.

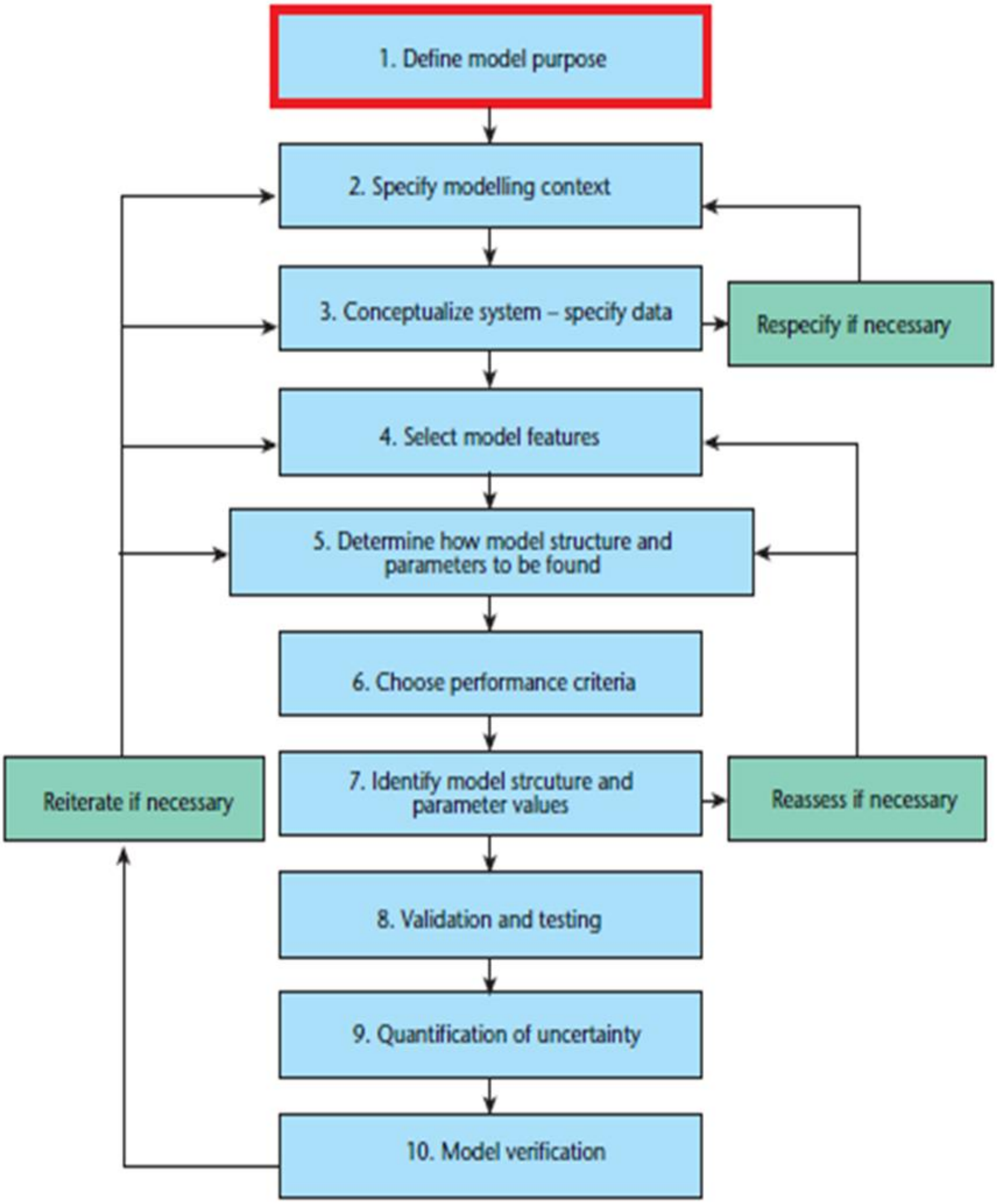


Fig. 2-2 Process for developing a flood forecasting model (WMO, 2011,[3])

Table 2-2. Operational Flood Forecasting Systems in use by selected agencies in World [1]

Country	Model	Model Characteristics	Rainfall input	Remarks	Reference
European Flood Awareness System (EFAS)	LISFLOOD-2D	GIS based spatially-distributed hydrological rainfall runoffmodel developed at the Joint Research Centre (JRC, European Commission) for operational flood forecasting	Numerical weather prediction (NWP) forecast	Fully operational since 2012. It provides pan-European overview maps of flood probabilities up to 15 days in advance, and detailed forecasts at stations where the national services are providing real-time data	https://www.efas.eu/ Thielen *et al.* (2009) The European Flood Alert System - Part 1: Concept and development, Hydro. E rth Syst. Sci., 13, 125-140 Bartholmes *et al.* (2009) The European Flood Alert System EFAS – Part 2: Statistical skill assessment of probabilistic and deterministic operational forecasts, Hydrol. Earth Syst. Sci., 13, 141–153
USA	HEFS consists of suits of model; Snow-17, Sacramento Soil Moisture Accounting model (SAC-SMA) and Unit Hydrograph approach	Snow-17 model for snow ablation - distributed energy balance model SAC-SMA - Spatially-lumped continuous soil moisture accounting model UH for flood routing	NWP ensembles	Operational through NWS (NOAA) for all lower USA	Demargne *et al.* 2014
CWC, India	Statistical / correlation techniques for most of the basins MIKE-11 FF models HEC-HMS	Statistical gauge to gauge, gauge & discharge correlations for some sites; multiple coaxial correlations using gauge and rainfall data Semi lumped for rainfall-runoff model and 1D flood routing model Distributed hydrological model	Rain gauge data and Antecedent Precipitation Index (API) datafor some stations. Real-time 3-hourlyhydrometeorological and daily ET data.	For most of basin in India Selected sites in Damodar Basin, Godavari Basin, Mahanadi Basin,and Chambal Basin, India. Godavari basin in India	http://nidm.gov.in/idmc/Proceedings/Flood/B2%20-% 2027.pdf CWC 2015. 'Flood Forecasting & Warning System in India', in Regional flood early warning system workshop, 23-27 November 2015, Bangkok.
Flood Warning system in Malaysia	WEHY, HEC RAS & MIKE 11	Physical based watershed Hydrology model (WEHY) and 1D flood routing models	(NWP) from Global Forecast System (GFS)	Rivers of Pahang, Perak and Golok, Malaysian Government web site	http://forecastmuar.water.gov.my/map
BWDB (Bangladesh)	MIKE 11	1-D hydrodynamic model	Radar altimeter measurement of river stage (Satellite-based flood-level observation in upper reach is used to increase lead time)		http://www.ffwc.gov.bd/, 20Workshop%20Proceedings-13Jan2016.pdf Bangladesh Water Development Board An e-service on Flood Forecasting & Warning in *Bangladesh* Flood forecasting & Warning center, WAPDA Building 8th. Floor Motijheel C/A, Dhaka-1000
Nepal	HEC-RAS MIKE NAM, MIKE 11	1 D hydrodynamic model Semi distributed hydrologic model & 1D hydrodynamic model	Web based telemetry system for real-time data acquisition. Rainfall forecast from weather rainfall forecast (WRF) model	West Rapti basin in Nepal. Bagmati Basin, Nepal	http://www.hydrology.gov.np/ new/bull3/index.php/ hydrology/home/main DHM 2015. 'Flood EWS Activities in Nepal', in Regional flood early warning system workshop, 23- 27 November 2015, Bangkok.
Philippines			Satellite-based rainfall estimates in addition to conventional raingauge, WRF		http://www1.pagasa.dost.gov.ph/ index.php/floods/general-flood-advisories
Pakistan	Sacramento model SOBEK model	Distributed hydrological model 1D hydrodynamic routing model	Real-time hydrometeorological data.	Models have been developed by Delft Hydraulic, Netherlands with inputsfrom National Engineering Services Pakistan.	Statistical modelling (http://wci.t.u-tokyo.ac.jp/events/ awcs2016/presen/3-1-7.pdf) IFAS was also developed for Upper, Middle and Lower Indus basin and handed over to FFD/PMD in 2014 http://www.pmd.gov.pk/FFD /index_files/ifashvd.htm

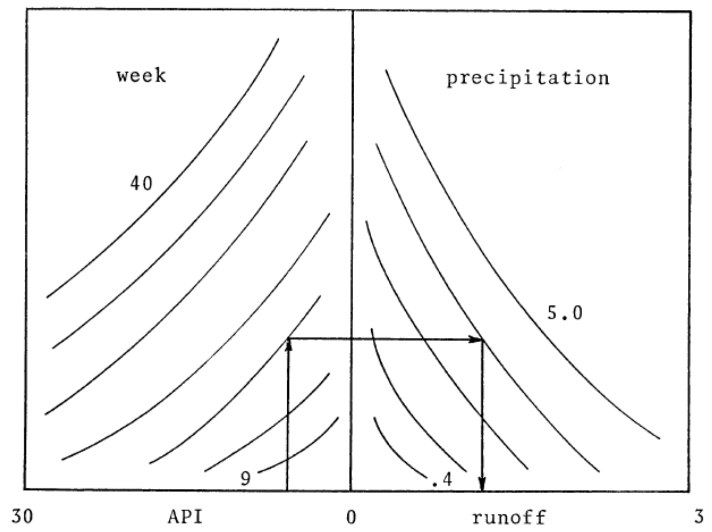


Fig. 2-3 A simple coaxial gragh for Ontario to Flood Forecasting [9]

Utilization the digital computer under the direction of a numerical opjtimization technique should make the coaxial correlation method more promising to minimize the error term of the final results for specific watersheds (Fig 2-4).

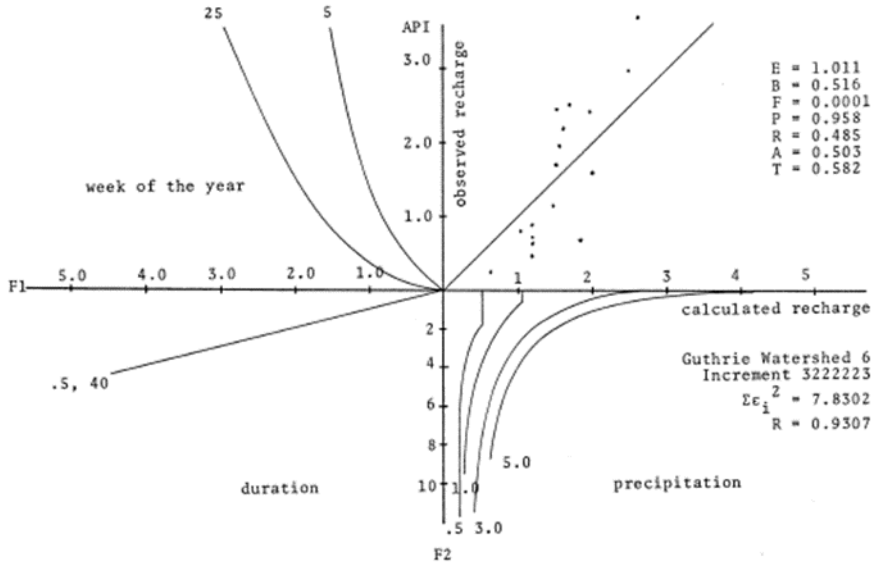


Fig. 2-4 A semi- sophisticated coaxial gragh to Flood Forecasting, Webster,1973 [9]

2-2-1-2- Flood routing

Forecasters can develope a large set of correlation, and coaxial diagrams which display the pattern of correlation exhibited by two or more variables (water level, travel time, discharge, rainfall, ...). Such charts are relatively less complex, and are quite popular among its users. Nevertheless, they need periodical updating to account for constant alteration in catchment characteristics and river regime. One out of several such diagrams used in Iran and India is shown here. When a number of tributaries affect the water level at the forecasting station, the variation in water level at base station (base station is a location upstream of forecast station) on the main river as well as base stations on the tributaries considered to prepare co-axial diagrams. One such diagram developed for formulation of forecast at Patna (Gandhighat) on river Ganga is shown in Fig.2-5. In this diagram, water level fluctuation at Patna takes into account the variation in water level at Buxar on river Ganga; Darauli on river Ghaghra; Chopan on river Sone; and Rewaghat on river Gandak.

This concept can also be extended to account for rainfall in upland area. Fig.2-6 is for formulating the forecasts at Khowang on river Brahmaputra considering rise and fall in water level at Naharkatia site.

Additionally, rainfall observation at Naharkatia is also accounted for to incorporate its likely influence to the water level at Khowang.

However, these charts carry limitations in that they provide only peak flow or water level information, and drop no hint about the shape of likely flood hydrograph at forecast site. This aside, there is absence of statistical test to measure the strength of correlation between dependent and independent variables. Nevertheless, such diagrams are proved quite useful in absence of fully developed network of hydro-meteorological stations; skilled personnel to operate sophisticated models; and seamless flow of data from remote locations to forecast centre.

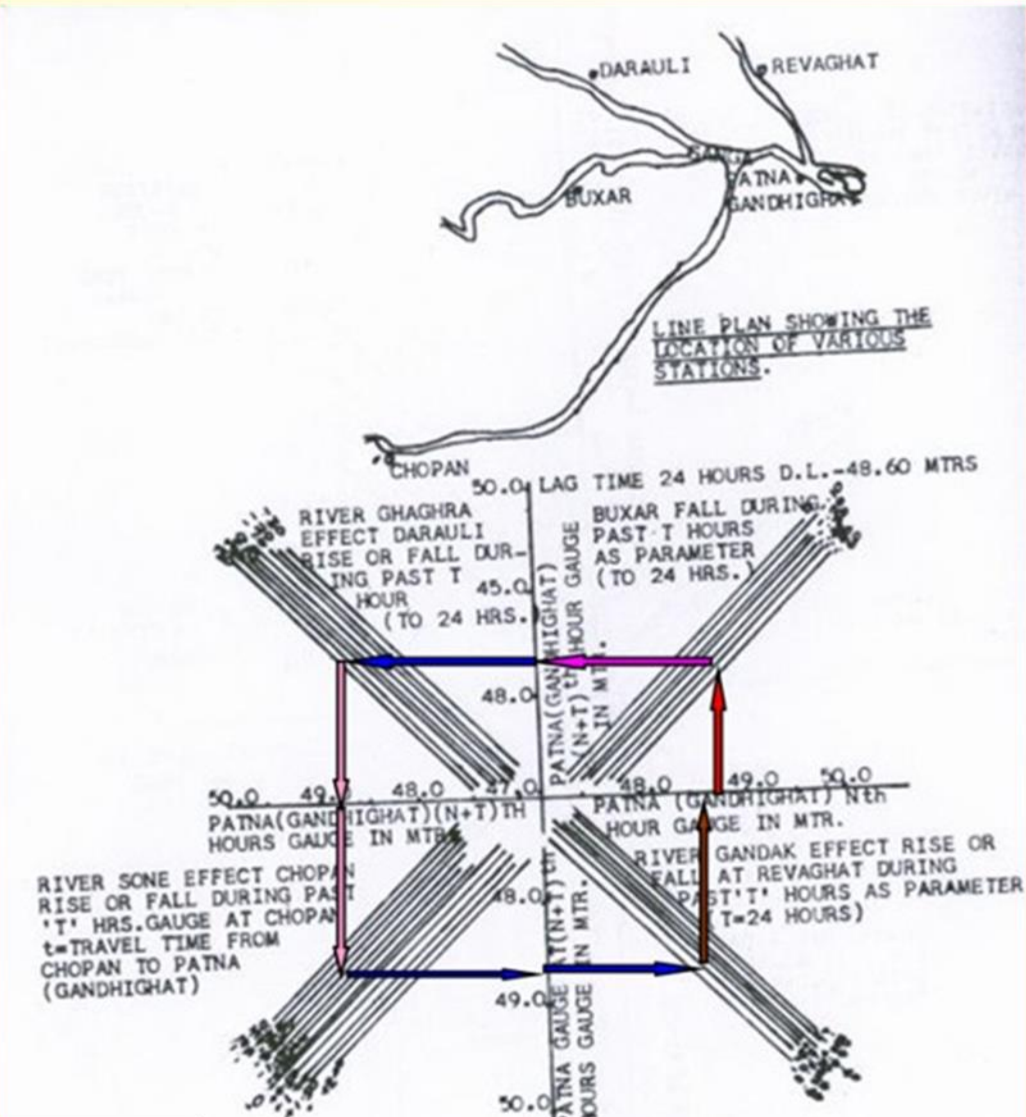


Fig.2-5

CORRELATION GRAPH FOR THE SITE PATNA (GANDHIGHAT) RIVER GANGA FALLING STAGE YEAR 1978.

Fig. 2-5 Correlation graph for site PATNA to flood forecasting in real time

Fig.2-6

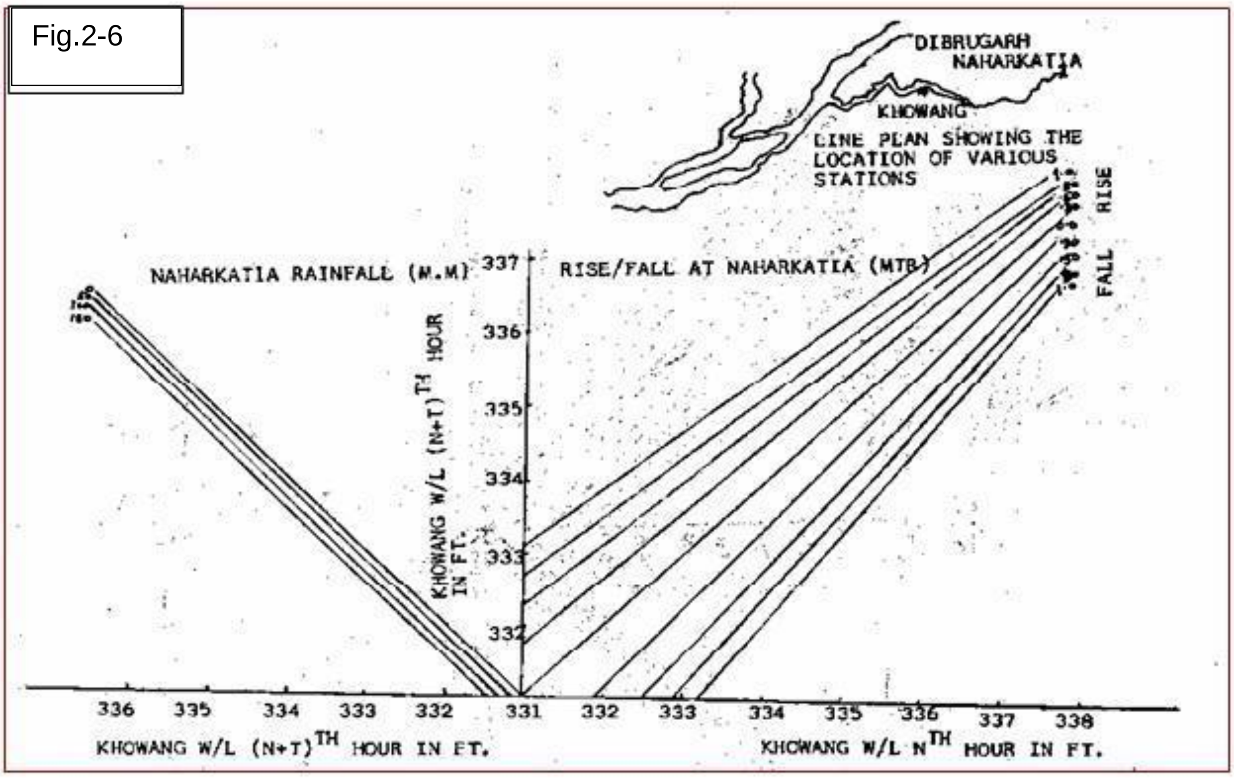


Fig. 2-6 Correlation graph for site Khowang to rainfall and flood forecasting in real time

2-2-2-Mathematical equations

2-2-2-1- Regression equations

This method defines relationship mathematically among variables by 'regression/multiple regression techniques'. The strength of such pattern is easily determined by correlation coefficient, 'r', and thus subjective judgment of a person in drawing a best-fit line is eliminated.

Mathematical equations offer much ease in calculation of dependent variable, and in turn speed up forecast process. Chart at Fig. 2-7 displays an equation that estimates water level at downstream location, Mahemdabad, Gujarat with change in water level at upstream site.

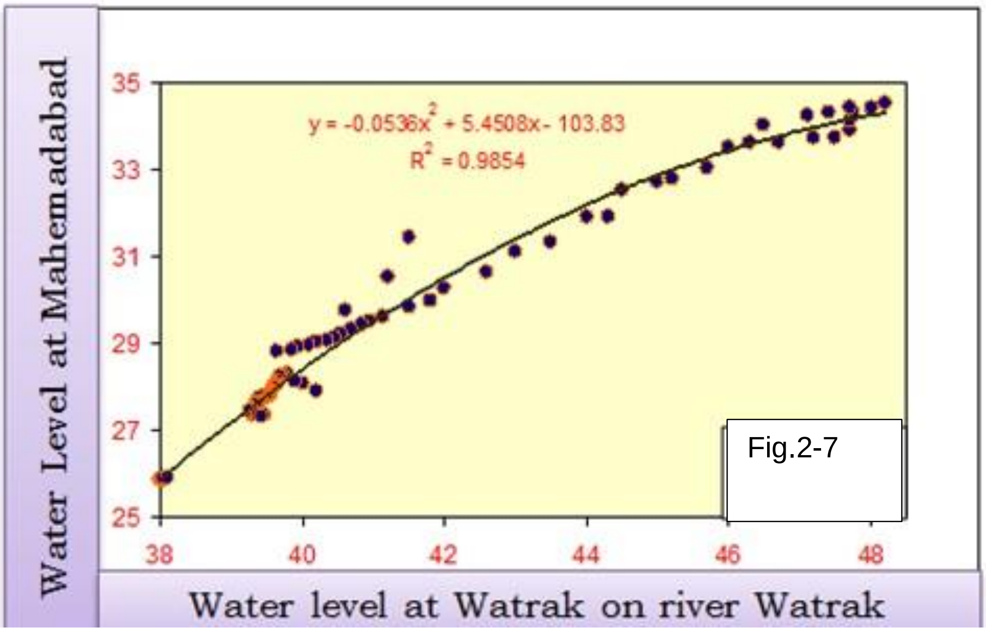


Fig. 2-7 Correlation equation to estimates water level at downstream location in real time

A respectable degree of r^2 as 0.9854 is achieved by introducing a time lag/shift of 4 hrs between two sets of data. The arrival of this time lag is based on output obtained through cross-correlogram technique or travel time. With no time lag, two sets of data are poorly correlated.

Another approach is to develop a mathematical model relating forecast station water level with water level of a tributary joining in-between base and forecasting station, and of base station. This method is elaborated by an example comprising three stations. Location of stations may be visualized as shown in Fig.2-8. Table 2-3 lists water levels observed at these locations.

A linear multiple regression equation with X1 as dependent variable and X2, X3 independent variables can be expressed as below.

$$X_1 = a + b\,X_2 + c\,X_3$$

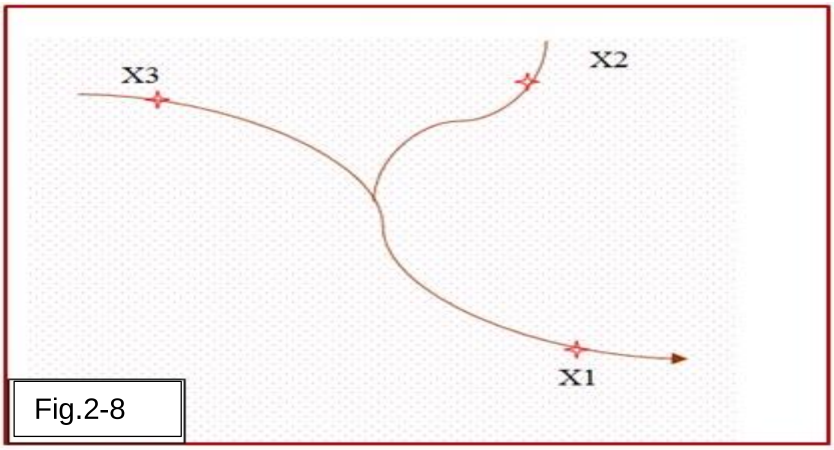


Fig.2-8

Fig. 2-8 Location of base (x3) and frecasting (x1) and tributary (x2) stations

Table 2-3. water levels observed at x1,x2 and x3 station

Water level at forecasting station in m (X1 observed)	*tributary water level in (X2)*	*water level at base station in m (X3)*	*X1 computed or Estimated*
80.3	112.2	165.3	80.6
80.5	112.2	165.8	80.6
82.2	112.7	166.6	82.0
84.3	113.3	167.2	83.6
85.6	114.0	168.0	85.5
85.7	114.1	168.4	85.8
86.0	114.3	168.8	86.3
86.3	114.3	169.3	86.3
87.1	114.6	170.2	87.1
$\Sigma X1$ = 758.0	$\Sigma X2$= 1021.7	$\Sigma X3$= 1509.6	
Standard Deviation = 2.578			Sest = 0.357

The coefficients a, b and c are estimated by the method of least square or of Matrix [A] containing all three unknown coefficients is solved by multiplying [R]-1 matrix with [X1] matrix.

$$[A] = [R]^{-1} [X1]$$

Results as bellow:

$$X_1 = -223.017 + 2.71\, X_2 - 0.0003\, X_3$$

Correlation coefficient, r for the defined equation is 0.99 suggesting higher degree of correlation among variables and can be adopted as forecast model.

Standard Deviation (SD) and S_est are needed to estimate r^2. To determine SD, reader may consult flood frequency module. S_estis determined by. $\Sigma(X_{i,\,obs} - X_{i,comp})^2/(n-2)$. Finally, r^2 is determined by following equation:

$$S_{est} = SD\ (\text{or } \sigma)\ \sqrt{}\,(1 - r\hat{}2\ )$$

Equation of the type X1 = a . X2 b1. X3 b2 .. can also be evaluated by converting them into a linear form by logarithmic transformation. Secondly, in the current example, two independent variables are water level. Reader can substitute it by other variables or add more variables to this equation. Solution of coefficients follows similar steps.

Another relationship derived by multiple regression technique determines the change in water level at forecast site bases on the variations recorded at two upstream sites, commonly known as base stations. While preceding equation relates water levels of two sites, this equation correlates variation in water levels at different sites.

2-2-2-2- Mathematical model based on Muskingum method

According to Muskingum Outflow Equation (after Hydrology by H M Raghunath), outflow and inflow at two time steps, (t+1) & t related to by equation (I).

$$O_{t+1} = C_0 I_{t+1} + C_1 I_t + C_2 O_t \quad \ldots\ldots (I)$$

For a few initial time steps of observed inflow hydrograph, such as I1, I2 ---, I4, and O1, O2 ---, O4 of outflow hydrograph, a set of equations, with the help of eq. (I) can be written as below:

$$(O_3 - O_2) = C_0 (I_3 - I_2) + C_1 (I_2 - I_1) + C_2 (O_2 - O_1) \quad \ldots\ldots (II)$$

$$(O_4 - O_3) = C_0 (I_4 - I_3) + C_1 (I_3 - I_2) + C_2 (O_3 - O_2) \quad \ldots\ldots (III)$$

Now, assuming that discharge and water level curves at either location a straight line; and denoting water level at upstream and downstream sites as H & G respectively (Fig. 2-9), we can say that:

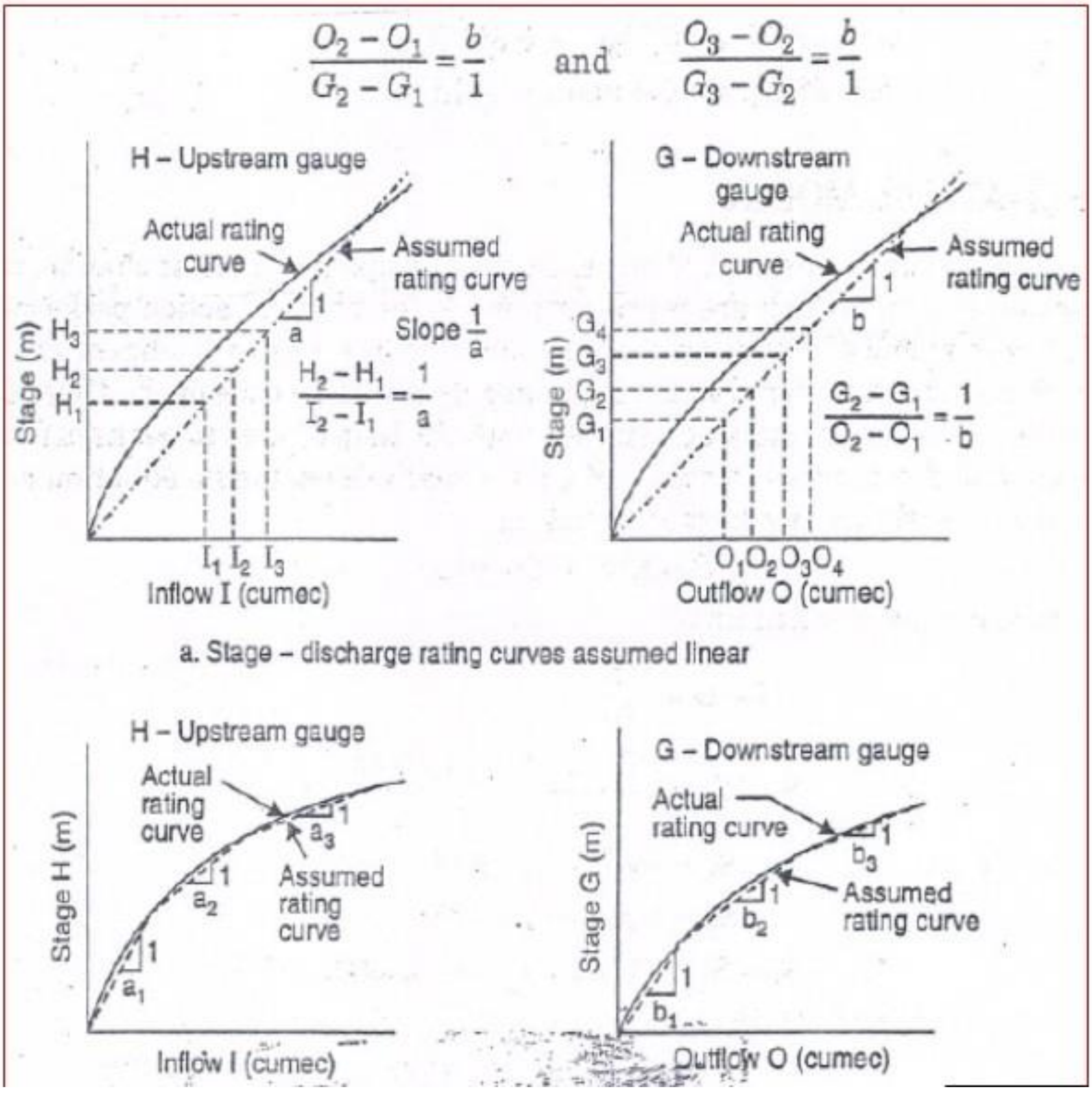


Fig. 2-9 Stage-discharge rating curves assumed linear

Replacing discharge component of equations (II) & (III) with this, we get:

$$(G_4 - G_3) = x_1 (G_3 - G_2) + x_2 .(H_4 - H_3) + x_3 . (H_3 - H_2) \ldots \text{(VI), or}$$

$$G_{4.3} = x_1 G_{3.2} + x_2 H_{4.3} + x_3 . H_{3.2}$$

Equation (VI) combines change in water level at downstream site with changes in water level at upstream site. At this stage, reader may please note thatsubscripts 4, 3, 2 in above equation denotes difference water level at time (t+1), t & (t-1) at respective stations. A set of equations,like this, may be obtained by suitably picking up data from observed hydrographs to estimate coefficients x1, x2, & x3 by matrix method as elaborated earlier. While doing so, it is highly recommended to check'r^2' value to ensure that model is worth for the purpose it is defined. This sort of equation can be developed <u>for rising and falling stages separately</u>. Further refinement is possible by dividing stages into two or three ranges with each range represented by unique equation (please see Fig.2-7). Additionally, equation (VI) considers only one station/site in the upstream. In case, water level at downstream site happens to be affected by more than one site, a modified Muskingum equation can be written as:

$$G_{4.3} = x_1 G_{3.2} + x_2 H_{4.3} + x_3 . H_{3.2} + x_4 H'_{4.3} + x_5 . H'_{3.2} + x_6 H''_{4.3} + x_6 . H''_{3.2}$$

Where, H, H', H'' represent water level at three upstream sites. Number of equations formed in this manner need to be solved for coefficients by matrix method. The steps involved in the process with same set of data used in previous example are illustrated below:

Step 1

With two independent variables (water level at two upstream sites) and one dependent variable (water level at forecast station), equation (VI) takes following form.

$$G_{4.3} = x_1 G_{3.2} + x_2 H_{4.3} + x_3 . H_{3.2} + x_4 H'_{4.3} + x_5 . H'_{3.2}$$

Step 2

With known water levels at respective sites (Fig. 2-8 & Table 2-3), a set of values each representing change in water level at various time interval is tabulated next in matrix form:

[G] (7 * 1)				[H] (7 *5)				[X] (5 * 1)
$G_{4.3}$		$G_{3.2}$	$H_{4.3}$	$H_{3.2}$	$H'_{4.3}$	$H'_{3.2}$		
1.7	=	0.2	0.5	0.0	0.8	0.5	$x_1=$	**0.87**
2.1	=	1.7	0.6	0.5	0.6	0.8	$x_2=$	**1.78**
1.3	=	2.1	0.7	0.6	0.8	0.6	$x_3=$	**-3.88**
0.1	=	1.3	0.1	0.7	0.4	0.8	$x_4=$	**-1.12**
0.3	=	0.1	0.2	0.1	0.4	0.4	$x_5=$	**2.55**
0.3	=	0.3	0.0	0.2	0.5	0.4		
0.8	=	0.3	0.3	0.0	0.9	0.5		

Please note that (7 * 1), (7*5) & (5 * 1) denote matrix size; G is water level at X1; H at X2; & H' at X2 site.

Values of coefficients are determined by solving the matrix by an equation given below.

$$[X] = [(H^T.H]^{-1}. [H^T].[G]$$

With coefficients indicted in above table, a mathematical equation takes following form for use in flood forecast:

$$G_{4.3} = 0.87G_{3.2} + 1.78\ H_{4.3} - 3.38\ H_{3.2} - 1.12\ H'_{4.3} + 2.55\ H'_{3.2}$$

While seeking to define an equation by this approach, caution is needed toward the inherent assumption associated with the method, i.e. a plot between water level and discharge should closely follow a linear trend in that range for which user/forecaster intends to relate parameters.

A comparison between observed vs. computed water level at X1 and relevant statistical parameters which measure the strength of model are presented in Table 2-4.

Table 2-4 Observed vs. computed water level at X1 and relevant statistical parameters

	Observed Water level at X1	Computed Water level at X1	(Obs -Com)^2
	82.2	81.9	0.066
	84.3	84.2	0.016
	85.6	85.7	0.006
	85.7	85.8	0.007
	86.0	86.3	0.107
	86.3	85.9	0.127
	87.1	87.4	0.069
Sd =	1.611861	Sest=	0.315
r =		0.98	

2-2-3-Hydrological Models

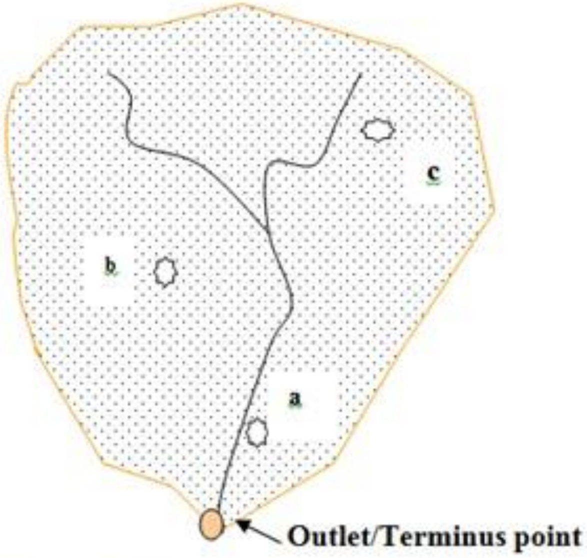
2-2-3-1-Rainfall-runoff models

a)Lumped models (CWC in 1989, p 239-244) and [10,11,12,13]

we can analysis flood hydrographs at a specific watershed to generate a unit hydrograhp with t-hr duration (Table 2-5) (based on storm duration steps) and generate or calculate losses based on rainfall-runoff analysis. As per the report received at 1900 hrs on 13th September, the average rainfall observed at different hours (Table 2-5) was as follows in the schematic basin (Fig. 2-10).

wherein 3-hr duration unit hydrograph (owing to 1mm effective rainfall over the basin/catchment) for a basin area of 8570 sqkm is given along with mean rainfall events over the basin. The base flow at the beginning of storm is 300 cumec.

Fig. 2-10



Schematic Diagram of basin with locations of three Rain gauges & its Outlet where advance warning is intended

Table 2-4 Unit hdrograph and rainfall amount in real time

Time (hrs.)	Unit Hydrograph (cumec)
0	0
3	8
6	34
9	103
12	130
15	141
18	119
21	83
24	59
27	40
30	28
33	20
36	14
39	8
42	4
45	2
48	0

Duration (Hrs.)	Rainfall Amount
09-12	19.4 mm
12- 15	20.0 mm
15-19	14.9 mm
Total Rainfall	**54.3 mm**

Additional information available is a diagram, Fig. 2-11 (based on historical data) correlating total rainfall and runoff in varying base flow conditions (shown right).

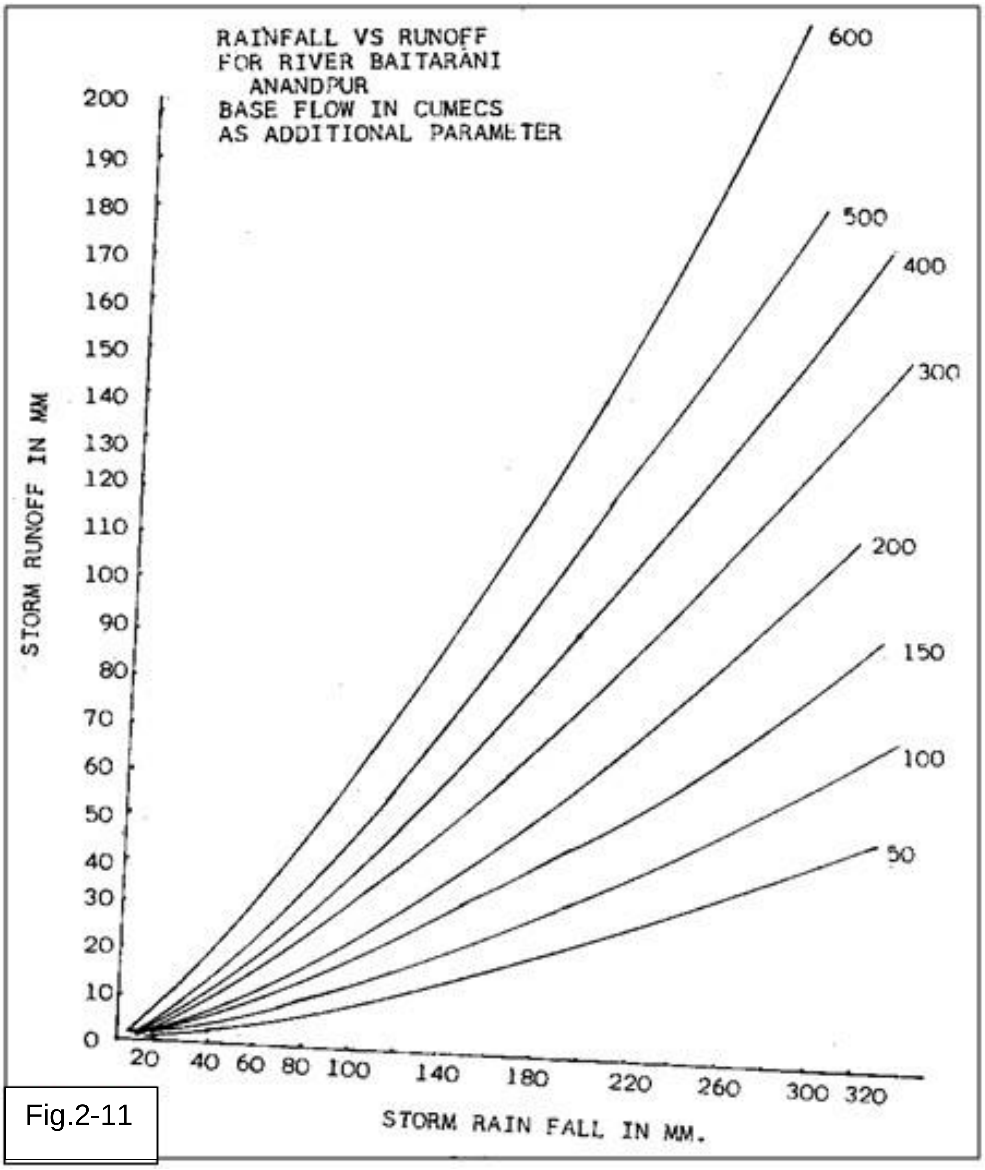


Fig.2-11

Fig. 2-11 Correlating total rainfall and runoff in varying base flow conditions

Referring to this diagram, runoff against a base flow of 300 cumec and 54.3 mm rainfall is 14.5 mm implying a loss of 39.8 mm during rainfall period. Form this, it is gathered that there is a loss rate of 4.43 mm per hour.

This point beyond, a model is developed in HEC-HMS by keying in information gathered as above (Fig.2-12). Basin in the model is represented by an element 'subbasin1'. This element hosts basin information; loss mechanism;transformation process and base flow contribution besides observed hydrograph at terminus point, if available (Fig.2-13).

Convolution of UH can be attempted in MS excel also. HEC-HMS software can be downloaded by visiting site http://www.hec.usace.army.mil/software/hec-hms/download.html , and is available for free.

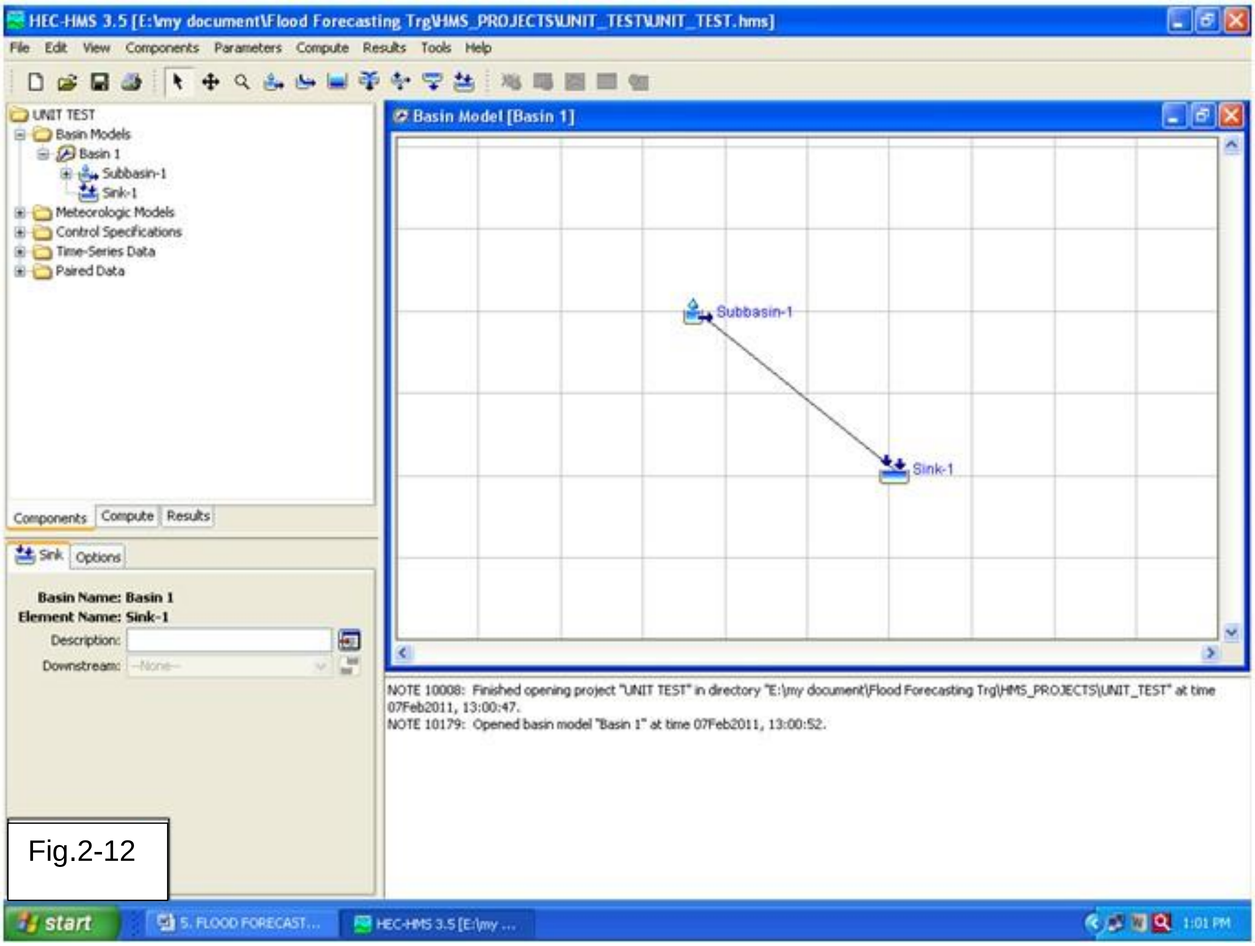


Fig. 2-12 Main window HEC-HMS 3.5

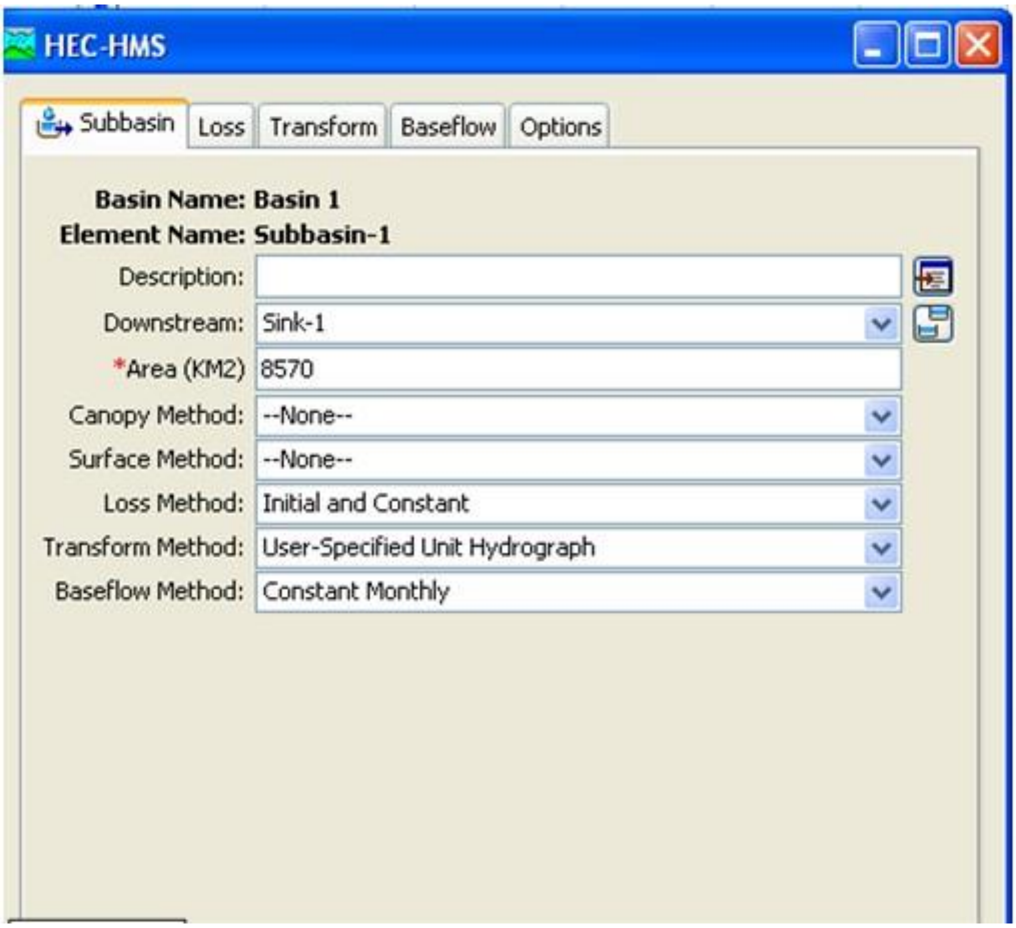


Fig. 2-13 Data entry in HEC-HMS 3.5

A elevation vs. discharge rating is also fed in the model, based on geometry data field and hydraulic studies in the interest reach to produce water level corresponding to variation in discharge at terminal location or in the interest rech.

In Fig 2-14 and Table 2-5 shows a set of output information that is quite handy for issuance of forecast ahead of its actual occurrence. Even though the ordinate's interval is every three hours in the current listing, user can elect appropriate interval to extract information of his desire.

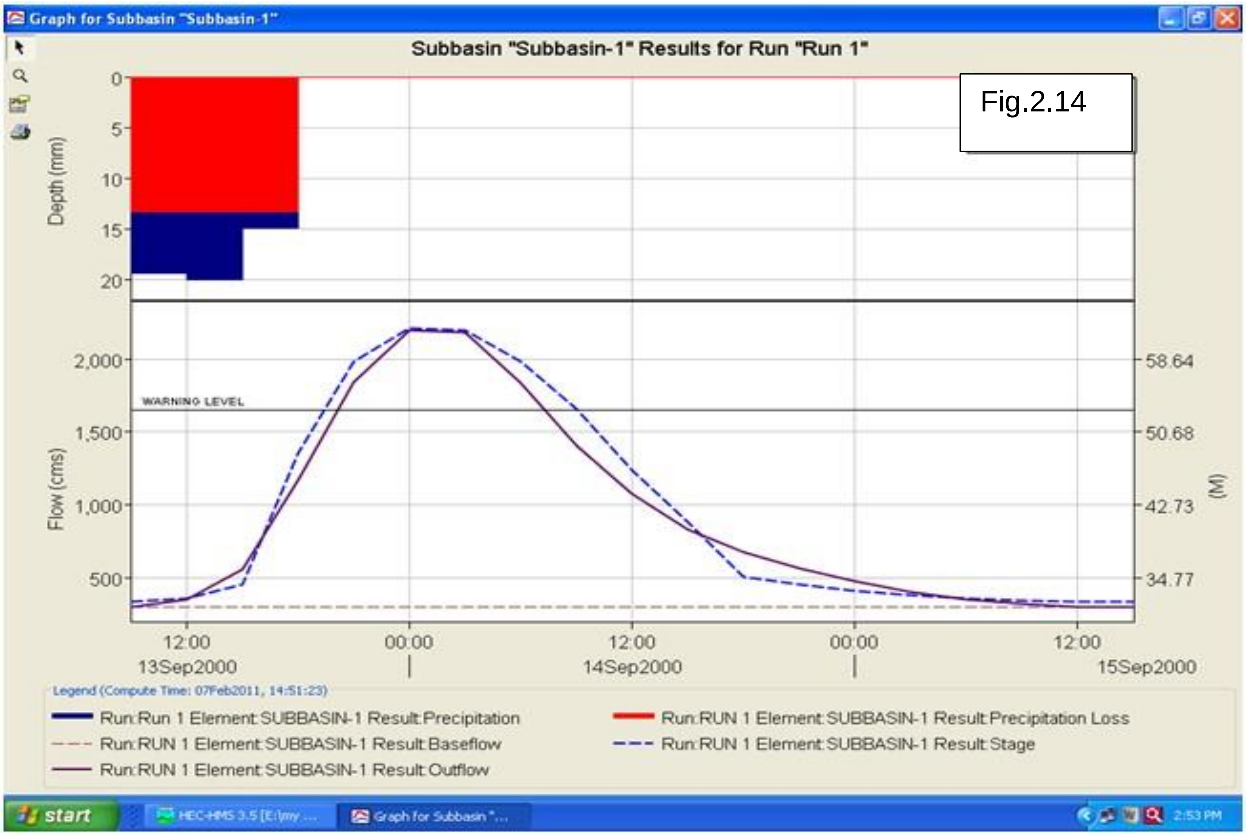


Fig. 2-14 Results for run1 at interest outlet in HEC-HMS 3.5

In above example, there are some challenges, when use a lumped model:

-A risk of overestimating the flood, when its convolution is based on average areal rainfall in large basins.

-Ignores likely impact of channel storage on flood attenuation

Table 2-5

Time-Series Results for Subbasin "Subbasin-1"

Project: UNIT TEST
Simulation Run: Run 1   Subbasin: Subbasin-1

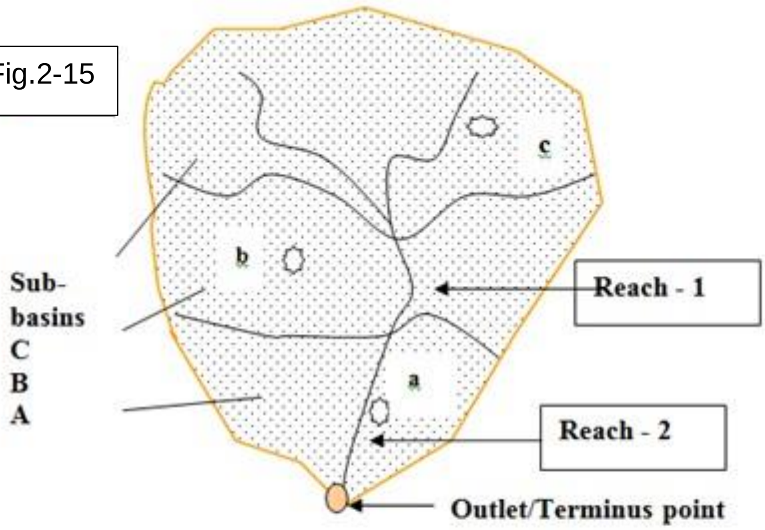
Start of Run: 13Sep2000, 09:00   Basin Model: Basin 1
End of Run: 15Sep2000, 15:00   Meteorologic Model: Met 1
Compute Time: 07Feb2011, 14:51:23   Control Specifications: Control 1

Date	Time	Precip (MM)	Loss (MM)	Excess (MM)	Direc... (M3/S)	Base... (M3/S)	Total... (M3/S)	Stage (M)
13Sep2000	09:00				0.0	300.0	300.0	32.1
13Sep2000	12:00	19.40	13.29	6.11	48.9	300.0	348.9	32.5
13Sep2000	15:00	20.00	13.29	6.71	261.4	300.0	561.4	34.0
13Sep2000	18:00	14.90	13.29	1.61	870.3	300.0	1170.4	48.4
13Sep2000	21:00	0.00	0.00	0.00	1540.2	300.0	1840.2	58.4
14Sep2000	00:00	0.00	0.00	0.00	1899.6	300.0	2199.6	62.0
14Sep2000	03:00	0.00	0.00	0.00	1882.5	300.0	2182.5	61.8
14Sep2000	06:00	0.00	0.00	0.00	1532.6	300.0	1832.6	58.3
14Sep2000	09:00	0.00	0.00	0.00	1109.0	300.0	1409.0	53.2
14Sep2000	12:00	0.00	0.00	0.00	773.9	300.0	1073.9	46.5
14Sep2000	15:00	0.00	0.00	0.00	534.5	300.0	834.5	40.9
14Sep2000	18:00	0.00	0.00	0.00	374.5	300.0	674.5	34.8
14Sep2000	21:00	0.00	0.00	0.00	264.8	300.0	564.8	34.0
15Sep2000	00:00	0.00	0.00	0.00	175.0	300.0	475.0	33.4
15Sep2000	03:00	0.00	0.00	0.00	100.7	300.0	400.7	32.9
15Sep2000	06:00	0.00	0.00	0.00	51.9	300.0	351.9	32.5
15Sep2000	09:00	0.00	0.00	0.00	19.9	300.0	319.9	32.3
15Sep2000	12:00	0.00	0.00	0.00	3.2	300.0	303.2	32.2
15Sep2000	15:00	0.00	0.00	0.00	0.0	300.0	300.0	32.1

b)Quasi-distributed models

The set of data inputted here remains the same as for previous case. Following illustration demonstrates, with the help of Fig. 2-15, application of UH in conjunction with MUSKNIGUM routing method to estimate magnitude of flood and time of its occurrence.

Fig.2-15



Basin partitioned into three parts. How to delineate it?
Various GIS based software offer excellent tools to perform this task quickly.

According to procedures illustrated in earlier example, UH considered for analysis represents an area of 8570 sqkm, and its convolution is based on average areal rainfall over the region. This concept of convolution of UH runs a risk of overestimating the flood because of departure from one of its fundamental assumption that rainfall is uniformly distributed over the region for a specified time. This may not be true for an area as large as 8570 sqkm. Additionally, this approach ignores likely impact of channel storage on flood attenuation. In order to adhere to this basic assumption, UH concept is usually applicable for an area less than or upto 5000 sqkm. We can overcomes this violation by sub-dividing the entire basin into three sub-basins A, B & C of area 2040 sqkm, 3470 sqkm and 3060 sqkm respectively, and assuming contribution of rain gauges a, b & c to respective sub-basins only. Accordingly, ordinates of UH has also been altered by a ratio between area of the respective part to the total area. Routing of flow along the reach is done by MUSKINGHUM method.

Parameters K, X have been taken from the example and its stability is ensured by adhering to constraint, such as 2KX should be less than T.

Additionally, equal contribution of 100 cumec as base flow from three parts is assumed. A basin delineated into three parts with two routing reaches is presented below. As discussed earlier, rainfall recorded at rain gauge 'c' contributes to sub-basin 'C', and therefore, its flood appears at basin outlet having propagated through reach -1 and reach -2. Similarly, sub-basin 'B' receives rainfall observed at rain gauge 'b', and resulting runoff travels through reach- 2 only. Sub-basin 'A' responds to rainfall at 'a', and its effect is visible at outlet (no routing is involved in this case).

In agreement with discussion in preceding paragraph, UH for each basin & Muskingum parameters for two reaches and rainfall excess at stations are given in Tables 2-6, 2-7 and 2-8.

A model (Fig. 2-16) duplicating three sub-basins and its reaches is created in HEC-HMS followed by data entry. HEC-HMS generated runoff at Outlet (Junction-2) appears at Fig. 2-17. Also shown there is change in water level according to fluctuation in discharge at this point of basin. Option is also available to mark warning level to distinguish critical period when there will be heightened risk because of swelling river.

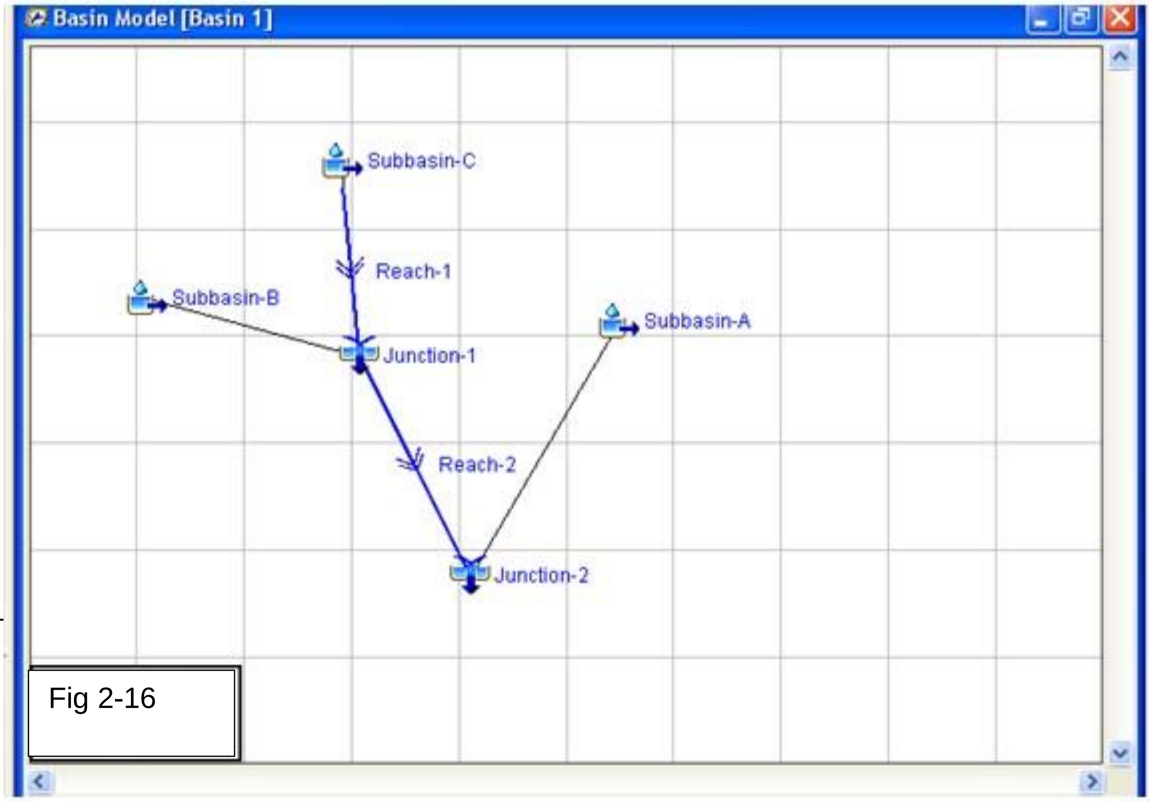


Fig 2-16

Table 2-6

Time in hrs	UH basin A	UH basin B	UH basin C
24:00:00	0	0	0
3:00	1.904	3.24	2.856
6:00	8.092	13.77	12.138
9:00	24.514	41.715	36.771
12:00	30.94	52.65	46.41
15:00	33.558	57.105	50.337
18:00	28.322	48.195	42.483
21:00	19.754	33.615	29.631
24:00:00	14.042	23.895	21.063
3:00	9.52	16.2	14.28
6:00	6.664	11.34	9.996
9:00	4.76	8.1	7.14
12:00	3.332	5.67	4.998
15:00	1.904	3.24	2.856
18:00	0.952	1.62	1.428
21:00	0.476	0.81	0.714
24:00:00	0	0	0

Table 2-7

Show Elements: All Elements Sorting: Hydrologic

Reach	Muskingum K (HR)	Muskingum X	Number of Subreaches
Reach-1	3	0.45	1
Reach-2	3	0.45	1

Apply Close

Table 2-8

Duration (Hrs.)	Effective Rainfall at 'a'	Effective Rainfall at 'b'	Effective Rainfall at 'c'
09-12	15.0	0.0	0.0
12- 15	0.0	14.0	2.7
15-19	0.0	0.0	12.3

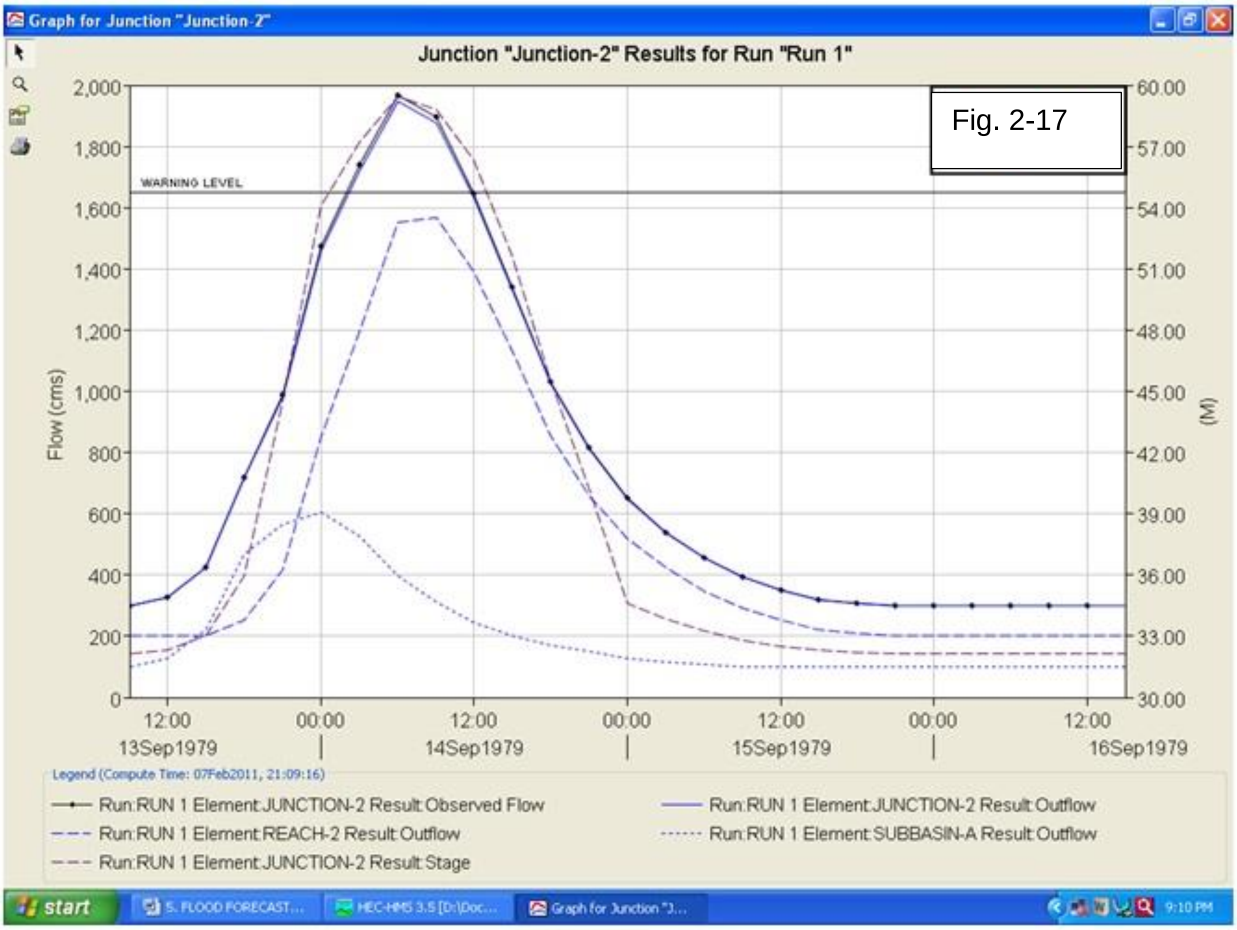


Fig. 2-17

Table 2-8 lists ordinates of flood hydrograph against time and compares with the observations. Options are also available in the HEC-HMS to observe resulting hydrographs for each and every element shown in model.

Table 2-8 Time-series results for interest points

Time-Series Results for Junction "Junction-2"

Project: FLOOD FORECASTING
Simulation Run: Run 1 Junction: Junction-2

Start of Run: 13Sep1979, 09:00 Basin Model: Basin 1
End of Run: 16Sep1979, 15:00 Meteorologic Model: Met 1
Compute Time: 07Feb2011, 21:09:16 Control Specifications: Control 1

Date	Time	Inflow from... (M3/S)	Inflow from... (M3/S)	Outflow (M3/S)	Obs Flow (M3/S)	Stage (M)
13Sep1979	09:00	200.0	100.0	300.0	300.0	32.1
13Sep1979	12:00	200.0	128.6	328.6	328.6	32.3
13Sep1979	15:00	202.2	221.4	423.6	423.6	33.0
13Sep1979	18:00	251.1	467.7	718.9	720.1	35.9
13Sep1979	21:00	417.4	564.1	981.5	986.8	44.5
14Sep1979	00:00	852.8	603.4	1456.1	1471.7	54.1
14Sep1979	03:00	1194.7	524.8	1719.5	1739.2	57.2
14Sep1979	06:00	1550.5	396.3	1946.8	1967.4	59.5
14Sep1979	09:00	1566.4	310.6	1877.0	1894.8	58.8
14Sep1979	12:00	1392.3	242.8	1635.1	1647.4	56.4
14Sep1979	15:00	1133.1	200.0	1333.1	1341.8	51.7
14Sep1979	18:00	855.0	171.4	1026.4	1032.4	45.5
14Sep1979	21:00	660.6	150.0	810.6	814.8	40.3
15Sep1979	00:00	520.0	128.6	648.6	651.6	34.6
15Sep1979	03:00	423.7	114.3	537.9	540.1	33.8
15Sep1979	06:00	348.2	107.1	455.3	456.5	33.3
15Sep1979	09:00	292.7	100.0	392.7	393.3	32.8
15Sep1979	12:00	251.4	100.0	351.4	351.7	32.5
15Sep1979	15:00	220.9	100.0	320.9	320.9	32.3
15Sep1979	18:00	209.1	100.0	309.1	309.1	32.2
15Sep1979	21:00	200.8	100.0	300.8	300.8	32.1
16Sep1979	00:00	200.1	100.0	300.1	300.1	32.1
16Sep1979	03:00	200.0	100.0	300.0	300.0	32.1
16Sep1979	06:00	200.0	100.0	300.0	300.0	32.1
16Sep1979	09:00	200.0	100.0	300.0	300.0	32.1
16Sep1979	12:00	200.0	100.0	300.0	300.0	32.1
16Sep1979	15:00	200.0	100.0	300.0		32.1

Print Close

Points to note:

- Regardless of duration of rainfall and its distribution over time, UH of known duration, say t-hr is to be fed in the HEC-HMS keeping its ordinates spaced at t-hr apart. For example, if UH of 1mm rainfall derived is of 3hr duration, ordinates of UH must be entered at 3hr interval. Software automatically converts this UH to duration according to rainfall distribution over catchment. This process rid us of steps needed for conversion of a UH from one duration to another.
- A relationship between stage/water level and corresponding discharge at forecast station is best represented by a rating curve or a power equation of the type $Q = c*(G-G0)^b$. Caution is required here to feed latest rating curve of the site in the software; which is best estimate of the prevailing river regime. Secondly, fitting a rating curve does need some technical skill. HYMOS software performs this task with ease.

c)Distributed models

Forecast estimated by applying hydrological models such as one presented in preceding paragraphs tends to vary widely from real values, where assumptions in unit hydrograph or routing models are violated by prevailing hydro-meteorological conditions over catchment. For example, rainfall is non-uniform over the basin and time distribution [10]; it is not stationary and moving across the basin; rainfall is concentrated in one pocket and leaving holes elsewhere. Apart from this, soil type and land-use pattern also vary over the catchment/basin that govern the rising and falling limb of resulting hydrograph. In lumped model, these characteristics are represented by a single SCS CN [11,12] applicable for entire area under study. Scenario,where spatial and temporal variations are dominating factors, demands application of distributed model to accurately capture the basin response.

Presented here is a distributed model developed and analyzed using Water Modeling System (WMS) and HEC-HMS. In this model, WMS software first delineates a watershed for an outlet point selected by the user, and thereafter creates grid (Fig. 2-18).

For each grid, it determines CN values according to its soil type and land-use cover layers by GIS tools. Once land component is over, software prepares a gridded precipitation database based on rainfall input provided by the user.

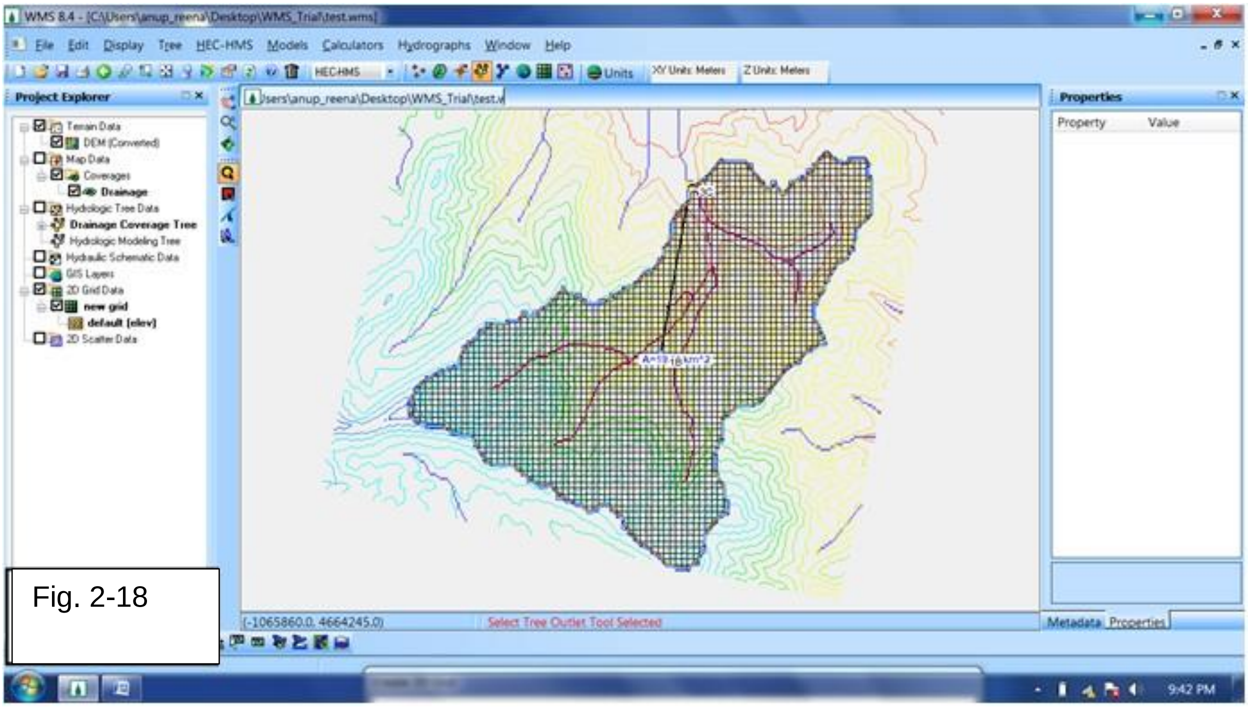


Fig. 2-18

A set of these gridded information are subsequently exported to HEC-HMS for simulation run or we can continue in WMS. HEC-HMS calculates the rainfall excess and route it to outlet by MODCLARK method for example (Fig. 2-19). A couple of screenshots display model set-up and results obtained at the end. WMS software can be downloaded by visiting site http://www.aquaveo.com/downloads.

2-2-3-2- Routing techniques (a)Lumped & b)Distributed models)

a)Lumped models

The Muskingum method of stream flow routing (Fig 2-20) is most frequently used because of its simplicity, as it works with known inflow hydrograph and some fitted parameters without seeking additional information. However, in order to get high degree of accuracy, this method should be for steady gradually varied flow and not in cases where reach is often affected by backwater or unsteady flow condition. The two fundamental equations for stream flow routing by Muskingum method are storage equation and Continuity Equation.

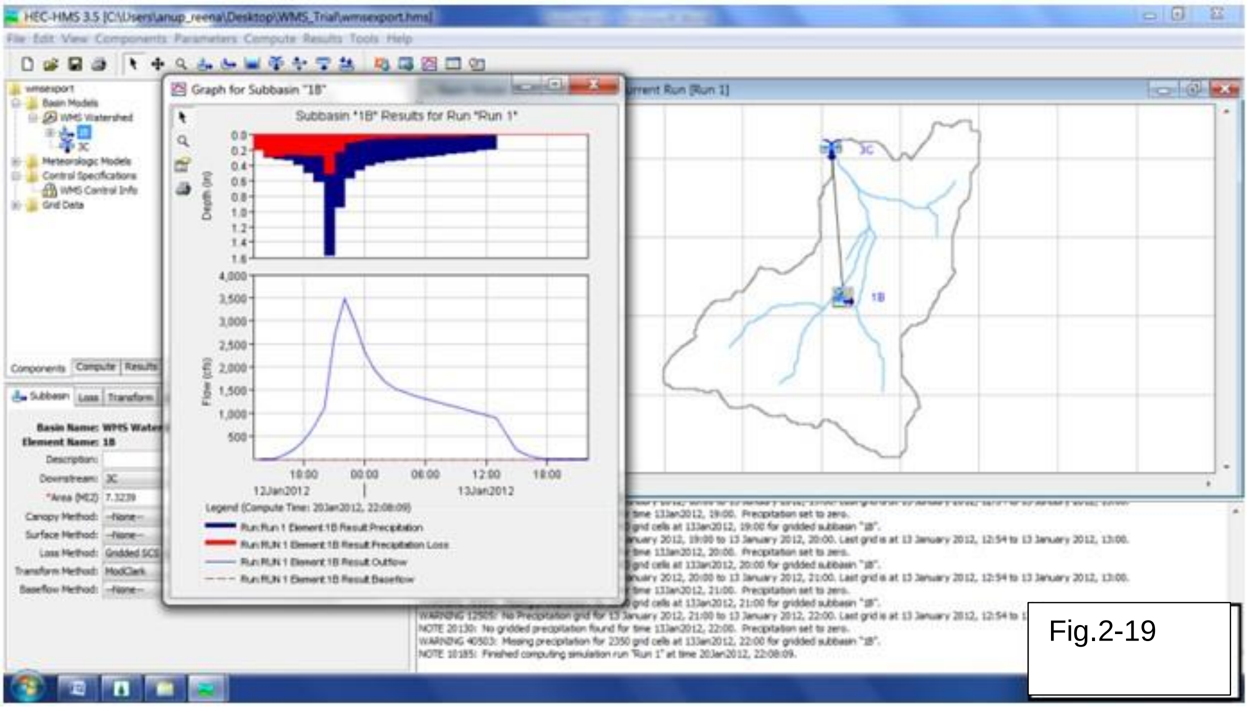


Fig.2-19

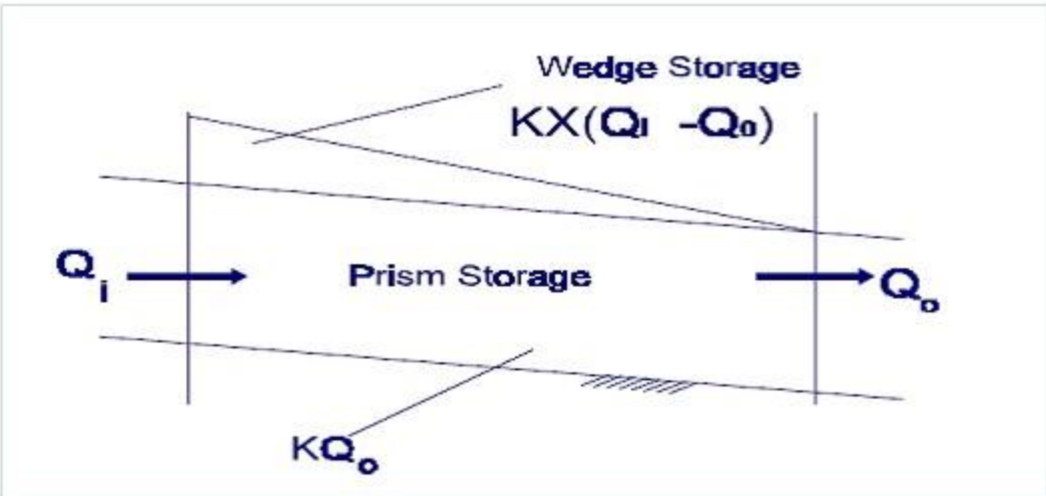


Fig. 2-20 Prism storage and Wedge storage in a river reach

Combining these two equations we get:

$O_{t+1} = C_o I_{t+1} + C_1 I_t + C_2 O_t$------------- (I)

The coefficients C_o, C_1 and C_2 are given respectively by

$C_0 = \frac{0.5\Delta t - Kx}{K - Kx + 0.5\Delta t}$	$C_1 = \frac{0.5\Delta t + Kx}{K - Kx + 0.5\Delta t}$	$C_2 = \frac{K - Kx - 0.5\Delta t}{K - Kx + 0.5\Delta t}$

The coefficients are connected by the relation:

$$C_o + C_1 + C_2 = 1$$

S = Prism storage + Wedge storage

$S = K.Q_0 + K.X.(Q1 - Q_0)$

Where,

S =	Total Storage
K=	A constant in time unit denotes the time of travel of flood wave through the reach. So, if flood wave velocity or celerity is C, C equals L/K, where L is reach length.
X =	A dimensionless factor which defines the relative weights given to inflow and outflow in determining storage. (Mostly varies between 0.1 & 0.3 and ranges between 0 & 0.5)
Q1 or $I_{t,\,t+1}$ =	Inflow rate at time t and t+1 , Δt
Q_0 or$O_{t,\,t+1}$ =	Outflow rate at time t and t+1, Δt

Equation (I) with known coefficients, Co, C1& C2 computes outflow with inflow and outflow at time t & t+1. However, accurate estimation/selection of K, X, Δt and subdivision of river reach is central to successful Muskingum routing, so merit due attention at the time of their estimation.

Determination of K and X

With Muskingum routing, the distance step, Δx, is defined indirectly by the number of steps into which a reach is divided for routing.

We will dig into example data set presented below (Table 2-9) to estimate these values. Later with HEC-HMS, optimized value for these parameters will be extracted. As with other models, $\Delta x/\Delta t$ is selected in a manner to approximate c, where c = average wave speed (also celerity) over a distance increment Δx.

If total reach length is L, and travel time is K, Wave speed, C is:

$$c = L/K = L/n.\Delta t$$

If there are n sub-reaches, and each sub-reach requires Δt time for discharge to flow past,

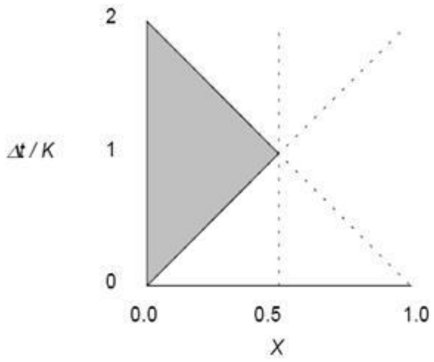
$K = n.\ \Delta t$

So, the number of steps,

$$n = K/\Delta t.$$

For current example, distance between two stations is around 112 km;an estimated value of K is assessed about 34 hour with table 2-9 (time interval between inflow peak and outflow peak- a rough estimation for K to begin with). Inflow flood hydrograph ordinates are at 2 hours interval, the routing reach should be divided in 17 steps, i.e. 34/2 to get the outflow hydrograph 112 km below. This leads to less attenuation as compared to routing carried out in a single step for the entire reach.

Secondly, the parameters K, X and computational time step ?t must also be selected in a manner so as to ensure that the Muskingum model/its coefficients must be rational. This implies that the parenthetical terms of the coefficients C1, C2 and C3 must be non- negative. To maintain this, values of K and X must be so chosen so that the combination falls within the shaded region shown below:



Optimal values of K and X for Muskingum method

Table 2-9 Time-series results for interest points

Date	Time	Inflow M^3/S at Japla on river Sone	Outflow M^3/S at Koelwar on river Sone
18-Aug-79	12:00	1,025.00	800
18-Aug-79	14:00	1,075.00	800
18-Aug-79	16:00	1,120.00	800
18-Aug-79	18:00	1,225.00	790
18-Aug-79	20:00	1,520.00	780
18-Aug-79	22:00	2,455.00	760
18-Aug-79	24:00:00	3,425.00	750
19-Aug-79	2:00	3,985.00	750
19-Aug-79	4:00	4,380.00	730
19-Aug-79	6:00	**5,035.00**	710
19-Aug-79	8:00	4,880.00	790
19-Aug-79	10:00	4,625.00	660
19-Aug-79	12:00	4,180.00	640
19-Aug-79	14:00	3,615.00	630
19-Aug-79	16:00	3,270.00	620
19-Aug-79	18:00	3,110.00	610
19-Aug-79	20:00	3,005.00	610
19-Aug-79	22:00	2,905.00	620
19-Aug-79	24:00:00	2,805.00	630
20-Aug-79	2:00	2,710.00	650
20-Aug-79	4:00	2,615.00	1,450.00
20-Aug-79	6:00	2,515.00	2,400.00
20-Aug-79	8:00	2,500.00	3,100.00
20-Aug-79	10:00	2,455.00	3,400.00
20-Aug-79	12:00	2,410.00	3,650.00
20-Aug-79	14:00	2,305.00	3,850.00
20-Aug-79	16:00	2,240.00	**3,930.00**
20-Aug-79	18:00	2,140.00	3,920.00
20-Aug-79	20:00	2,020.00	3,870.00
20-Aug-79	22:00	1,910.00	3,790.00
20-Aug-79	24:00:00	1,800.00	3,650.00
21-Aug-79	2:00	1,715.00	3,530.00
21-Aug-79	4:00	1,630.00	3,400.00
21-Aug-79	6:00	1,540.00	3,360.00
21-Aug-79	8:00	1,530.00	3,320.00

Bold value indivates, peak flow

In other words, K, X & Δt must satisfy a condition given by:

$$2KX \le \Delta t \le 2K(1-X)$$

Parameters chosen in violation of this condition produce an un-stable solution and HEC-HMS will prompt the user in its message box accordingly.Against this backdrop and selected K and Dt, estimated X is 0.03 **($\Delta t/2K$).**

Having defined Muskingum parameters, application of HEC-HMS in routing a reach by Muskingum method is demonstrated. A displays the river network and its feeding boundary developed using Geo-HMS extension installed on ArcView software, and a model set up in the HEC-HMS. Routing parameters for reach entered in HEC-HMS is exactly the same as deliberated above (Fig.2-21).

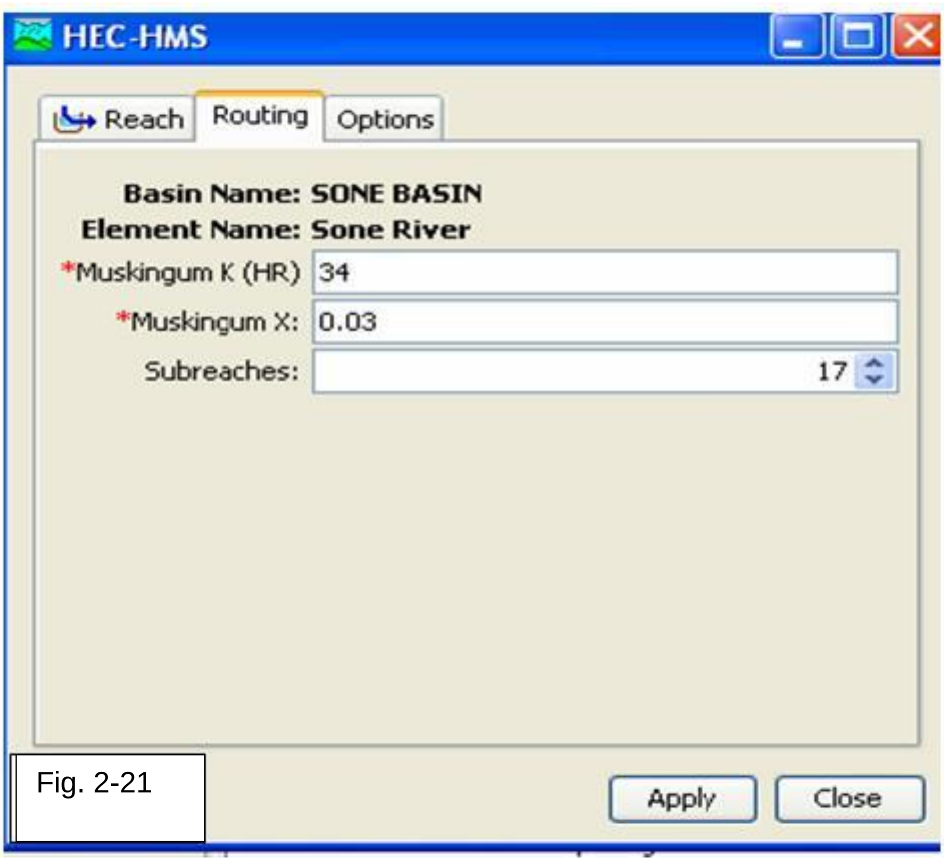


Fig. 2-21

After first 'Run', plots the simulated result against observed discharge at downstream end along with variation in water level (water level vs. outflow relation used here is made-up one, and is used for demonstration purpose only). The water level profile can be picked up for forecast purpose. As shows in Fig. 2-22 estimation value of debit of peak flow in outlet is 3747 cms against in observed hydrogragh is 3930 cms.

Fig. 2-22

At this stage, HEC-HMS offers another useful tool to optimize Muskingum parameters having finished first 'Run'. Fig.2-23 displays initial and optimized values of Muskingum parameters along with simulated and observed outflow, which is a slight improvement upon first 'Run'. Reader may adopt this new set of parameters to finalize their model for forecasting trial.

In this situation, estimated value and observed value close to each other. This process (Sensitivity analysis) can be do by calibration, verification and validation process that describe in flowing sections [2].

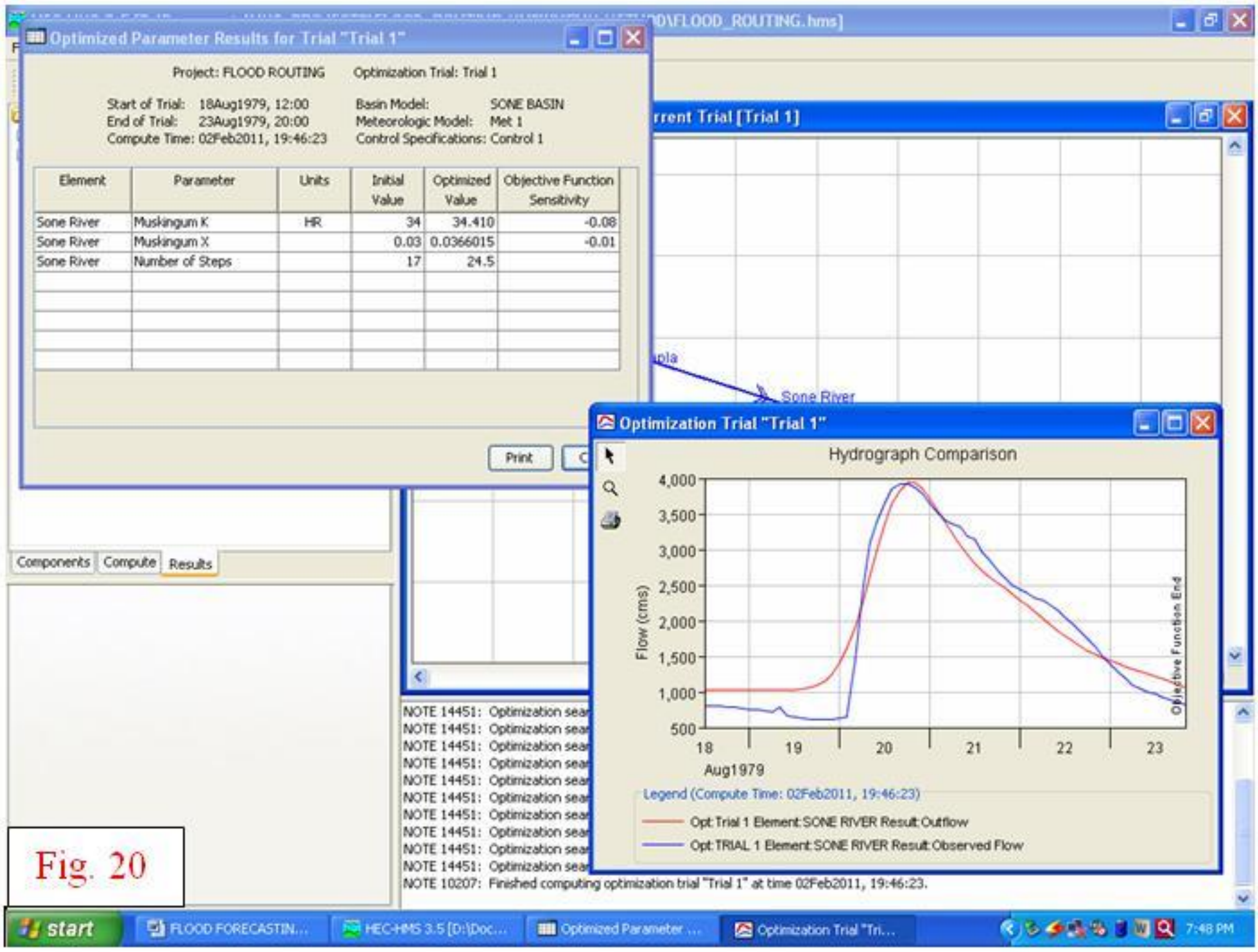


Fig. 2-23 Sensitivity analysis to optimize K & X estimation in Muskingum parameters

In doing so, it must be noticed that river regime is not a fixed entity over time and tends to exhibit continual changes in its course, geometry. That is why it had better develop a model based on flood events occurred recently or updating models (2-3), and discard earlier model to eliminate possibility of large variation in forecast value.

b)Distributed

Muskingum method operates with steady or gradually varied flow, and does not reveal any information in between the base and forecast station. That is why it is also termed as 'Lumped model'. If the forecaster intends to gather water profile and its propagation along river reach, distributed models, such as Muskingum-Cunge, or Kinematic Wave could be alternatives. keen readers may refer to 'Technical Reference Manual' of HEC-HMS or [2] for more information about it.

2-2-4-Hydraulic Models

2-2-4-1- Dynamic wave routing technique

HEC-RAS software is a one-dimensional flow hydraulic model designed to aid hydraulic engineers in channel flow analysis and flood-plain determination to perform a unsteady flow simulation for flood forecasting with use GIS RAS mapper for flood delineation. This software is available for free, from web-page:

http://www.hec.usace.army.mil/software/hec-ras/hecras-download.html .

Hydraulic routing employs the full dynamic wave (St. Venant) equations. These are the continuity equation and the momentum equation, which take the place of the storage-discharge relationship used in hydrologic routing. The equations describe flood wave propagation with respect to distance and time. Henderson (1966) rewrites the momentum equation as follows to 1-D:

$$S_f = S_0 - \left(\frac{\partial y}{\partial x}\right) - \left(\frac{V\partial V}{g\partial x}\right) - \frac{1}{g}\frac{\partial V}{\partial t}$$

Where,

S_f = friction slope (frictional forces), in m/m;

S_o = channel bed slope (gravity forces), in m/m;

2nd term = pressure differential;

3rd term = convective acceleration, in m/sec^2;

Last term = local acceleration, in m/sec^2

Also, we can rewrite it:

$$q = A(\frac{\partial V}{\partial x}) - (VB\frac{\partial y}{\partial x}) - B\frac{\partial y}{\partial t}$$

The description of each term:

$A(\frac{\partial V}{\partial x})$ = prism storage

$VB(\frac{\partial y}{\partial x})$ = wedge storage

$B(\frac{\partial y}{\partial t})$ = rate of rise

q = lateral inflow

Assumptions

The assumptions given bellow for all hydraulic models (one-dimensional flow, fixed channel, constant density, and resistance described by empirical coefficients) apply to dynamic routing. It is also assumed that the cross sections used in the model fully describe the river's geometry, storage, and flow resistance. The full dynamic wave equations are considered to be the most accurate solution to unsteady, one dimensional (1-D) flow, but are based on the following assumptions used to derive the equations (Henderson, 1966):

- Velocity is constant and the water surface is horizontal across any channel section.
- Flows are gradually varied with hydrostatic pressure prevailing such that vertical acceleration can be neglected.
- No lateral circulation occurs.
- Channel boundaries are considered fixed and therefore not susceptible to erosion or deposition.
- Water density is uniform and flow resistance can be described by empirical formulae (Manning, Chezy) Solution to the dynamic wave equations can be divided into two categories: approximations of the full dynamic wave equations, and the complete solution.

Fully Dynamic Wave Routing solution

Complete hydraulic models solve the full Saint Venant equations simultaneously for unsteady flow along the length of a channel. They provide the most accurate solutions available for calculating an outflow hydrograph while considering the effects of channel storage and wave shape (Bedient and Huber, 1988). The models are categorized by their numerical solution schemes which include characteristic, finite difference, and finite element methods[2]. The finite difference method describes each point on a finite grid by the two partial differential equations and solves them using either an explicit or implicit numerical solution technique. Explicit methods solve the equations point by point in space and time along one time line until all the unknowns are evaluated then advance to the next time line (Fread, 1985). Implicit methods simultaneously solve the set of equations for all points along a time line and then proceed to the next time line (Liggett and Cunge, 1975). The implicit method has fewer stability problems and can use larger time steps than the explicit method. Finite element methods can be used to solve the Saint Venant equations (Cooley and Mom, 1976). The method is commonly applied to two-dimensional models.

Limitations

The major drawback to fully dynamic routing models is that they are time-consuming and data intensive, and the numerical solutions often fail to converge when rapid changes (in time or space) are being modeled. This can be addressed by adjusting the time and distance steps used in the model [2]; sometimes, however, memory or computational time limits the number of time and distance steps that may be used. Additionally, fully dynamic one-dimensional routing models do not describe situations (such as lakes and major confluences) where lateral velocities and forces are important.

Stability of the model

The vital factors which affect the model stability and numerical accuracy are:

1. Cross Section Spacing
2. Computation time step
3. Theta weighting factor
4. Solution iterations & tolerances

Cross sections should be placed at representative locations to describe the changes in geometry. Additional cross sections should be added at locations where changes occur in discharge, slope, velocity, and roughness. Cross sections must also be added at levees, bridges, culverts, and other structures. Bed slope plays an important role in cross section spacing. Steeper slopes require more cross sections. Streams flowing at high velocities may require cross sections on the order of 30m or less. Larger uniform rivers with flat slopes may only require cross sections on the order of 300m or more.

Theta is a weighting applied to the finite difference approximations when solving the unsteady flow equations. Theoretically Theta can vary from 0.5 to 1.0. However a practical limit is from 0.6 to 1.0. Theta of 1.0 provides the most stability. Theta of 0.6 provides the most accuracy. The default in RAS is 1.0. Once the model is developed, reduce theta towards 0.6, as long as the model stays stable. The stability problems are due to:

1. Too large time step.
2. Not enough X-sections
3. Model goes to critical depth - RAS is limited to subcritical flow for unsteady flow simulations. Bad d/s boundary condition (i.e. rating curve or slope for normal depth). Bad X- section properties, commonly caused by: levee options, ineffective flow areas, Manning's n values, etc.

If this happens, note the simulation time when the program either blew up or first started to oscillate. Turn on the "Detailed Output for Debugging" option and re-run the program. View the text file that contains the detailed log output of the computations. Locate the simulation output at the simulation time when the solution first started to go bad. Find the river station locations that did not meet the solution tolerances. Then check the data in this general area.

Calibration of the Model

The model can be calibrated by changing the hydraulic parameters. Open Unsteady flowanalysis>Options>Computation options and tolerances. The theta (implicit weighing factor) value in hec-ras can be changed from 0.6 to 1 and repeated simulations can be run with changed iterations and Changed Manning's N to validate the actual results. Some Manning's N values have been cited from the literature, but the actual values are to be calibrated to have the model match with the real conditions[2]. We can also set the initial conditions during simulation and write detailed log output for debugging by clicking options> Output Option[2].

Executing the Model

The present simulation yielded very fitting results as regards discharge, but the water level difference remained at 22cms (529.37m simulated against 529.15m obs) (Fig 2-24). The simulated matching results may be because of the single reach simulation, recent observed X-sections and no other streams joining the reach except at Sangam. Further, this might have accrued due to the exact observed data input at the X-section points.

It is to note that the simulated value is $1674.38\ \mathrm{m^3/s}$ against the actual observed value of $1674.34\ \mathrm{m^3/s}$ at Kurundwad river (X-section_1)(0800 hrs on 2nd July, 2006, i.e, end of simulation period). The simulated water level is 529.37m against observed value of 529.145 m that mentioned above.

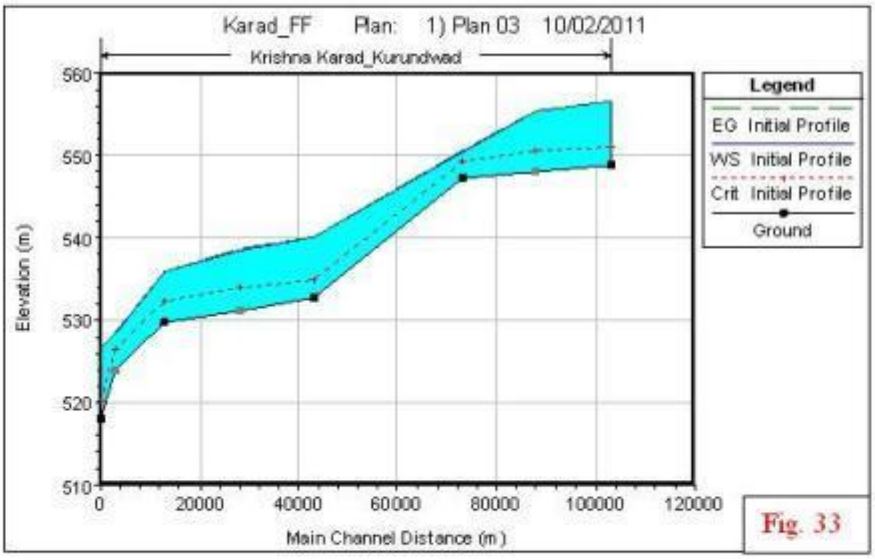


Fig. 2-24 Result of the simulated water level in Hec-Ras 4.1.0

2-2-5-Data driven hydrologic models

Sometimes,it is argued that deterministic, reductionist models are inappropriate for real-time forecasting because of the inherent uncertainty that characterizes river catchment dynamics and the problems of model overparameterization or time consuming. Moreover some uncertainties relevant to description parameters, understand only based on fuzzy and data diven models [2]. The advantages of alternative, efficiently parameterized data-based mechanistic models, identified and estimated using statistical methods, are discussed. An elementary brief part of ANN has been added here in the distance learning course for easy insight, though there are advanced architectures like recurrent neural network (RNN), radial basis function (RBF),self-organizing map (SOM) and othersused in flood forecasting.

2-2-5-1- Artificial neural networks

An artificial neural network is nothing but a collection of interconnected processing elements (PEs). The connection strengths, also called the network weights, can be adapted such that the network's output matches a desired response (Fig 2-25).

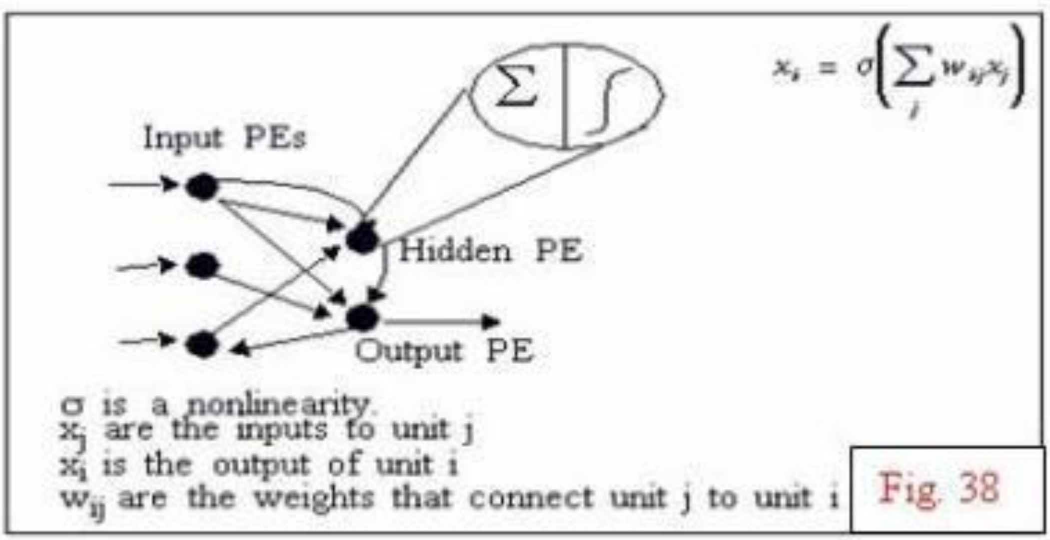


Fig. 2-25 Typical architecture of single hidden layer neural network

Fig. 2-25 depicts a typical multilayer perceptron, for example, which resembles a black box model, where a set of a data like x1, x2, x3…xn are fed directly to the network through the input layer, and subsequently produces expected result y in the output layer. The output is determined by the architecture of the network.

In multi-layered perceptron, hidden layer means a third layer of processing elements or units in between the input and output layers that increases computational power. In principle, the hidden layer can be more than one layer. In practice the number of neurons in this layer is evaluated by trial and error. Hornik et al. (1989) proved that a single hidden layer containing a sufficient number of neurons can be used to approximate any measurable functional relationship between the input data (debit, rainfall,..) and the output variable (water level, …) to any desired accuracy. In addition, De Villars and Barnard (1993) showed that an ANN comprising of two hidden layers tends to be less accurate than its single hidden layer counterpart. In this, a single hidden layer ANN has been used.

Each input xi (i =1,…,n) is attenuated by a factor wij, more commonly called a weight of the network, which is associated with the connection linking input xi to hidden neuron j (j = 1,….,k), where, k is the number of neurons in the single hidden layer. The weighted sum of the incoming signals entering a neuron is fed via an activation function, which is non-linear, producing a value that in turn, act as an input signal sent to the output layer. This is repeated for the output weights. The following expression gives the output value of the network.

$$y = \psi\left[\sum_{j=1i}^{N} \varphi\left\{\sum_{i=1}^{N} x_i w_{ij}\right\} a_j\right] \qquad (1)$$

Where, the sigmoidal activation function Ψ is given by:

$$\psi(x) = \frac{1}{1+e^{-\alpha x}} \qquad (2)$$

his function given at eq. 2 is a continuous function that varies gradually between asymptotic values 0 and 1 or -1 and +1. Where, α is the slope parameter, which adjusts the abruptness of the function as it changes between the two asymptotic values. Sigmoid functions are differentiable, which is an important feature of neural network theory.

To obtain the best approximations, it is needed to determine the optimum set of weights wij and aj that will yield the least mean square value of the desired response. Thus the following performance criterion needs to be satisfied.

$$\min_{a_j\ w_{ij}} \frac{1}{2} E\left[(y - y_D)^2\right] \qquad (3)$$

Normalization of the data

It is mentioned that the sigmoidal function can take the values ranging in the (0, 1) domain, a normalisation of the values of the input variables are done.

Numerous goodness of fit statistical criteria are proposed in the literature for evaluating hydrological modelling results. Two of these are, namely RMSE, and Nash - Sutcliffe coefficient (1970).

$$\text{Nash} = 1 - \frac{\sum_{i}^{N} (Y_o - Y_p)^2}{\sum_{i}^{N} (Y_o - \bar{Y}_o)^2} \qquad (7)$$

Where, Y_o = Observed daily gauge of the catchment on day i;
Y_p = Predicted daily gauge of the catchment on day i;

As could be seen from Fig 2-26, the model proved their capability in predicting the data, especially the stage data, which shows a high correlation of the observed and predicted data (Fig. 2-28).

ANN techniques can develop and solution in MATLAB software.

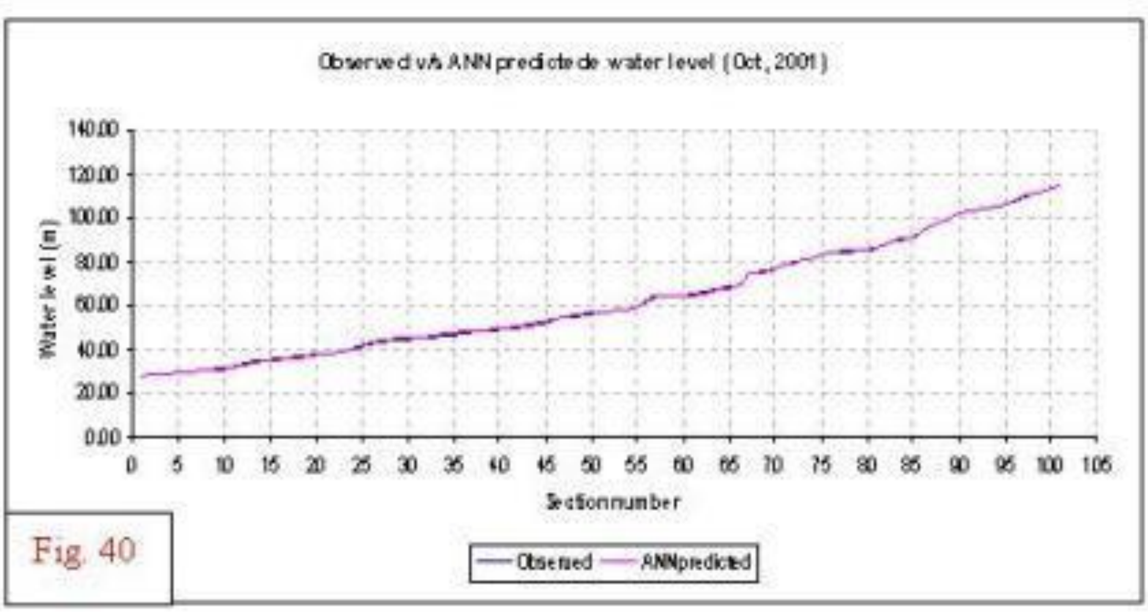


Fig. 2-26 predicting the water level with ANN

2-2-5-2- Fuzzy expert system design for flood forecasting

The platform for the fuzzy logic expert system can be MATLAB and MATLAB'S Fuzzy Logic Toolbox. Daliri & et,al.,(2013) developed a semi-fuzzy method (DSM) to priority flooding intensity based on interest parameters. In FF techniques, we must some years of average hourly stage data and expert knowledge are used to create a rule base for the fuzzy logic model. Rules are defined for both the high and low extreme conditions, with regard to actual occurrences, because of the physical nature of the relationships. Depending on number of membership functions for each input variable; the minimum rule base is created. For each data point, all rules are evaluated. The fuzzy logic and ANN models are evaluated based on their ability to predict the discharge (Fig 2-28).

2-2-5-3- ANFIS (Adaptive Neuro-Fuzzy Inference System) models

The hybrid system of learning has been attempted at combining ANN and fuzzy logic for developing the stage-discharge relationship to achieve a faster rate of convergence by controlling the learning rate parameter with fuzzy rules.

The objective is to get a minimizer, which has a low computing cost and a large convergence domain. This learning ability is achieved by presenting a training set of different examples to the network and using learning algorithm, which changes the weights in such a way that the network reproduces a correct output with the correct input values. The main dissimilarity between fuzzy logic system (FLS) and neural network is that FLS uses heuristic knowledge to form rules and tunes these rules using sample data, whereas NN forms "rules" based entirely on data. Learning rate control by fuzzy logic has been depicted at Fig 2-27. (FLC - fuzzy logic controller, MLP - multilayer perceptron).

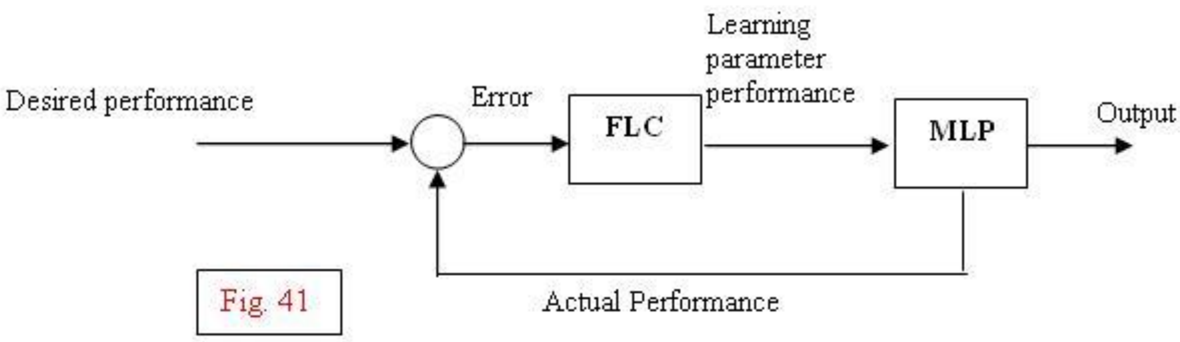


Fig. 2-27 Learning rate control by fuzzy logic

Validation and comparison of results

The ANN, fuzzy and neuro-fuzzy models thus developed is validated and compared with the observed data points and the statistical measures of goodness-of-fit of the neuromorphic models. Numerous goodness of fit statistical criteria are in literatures for evaluating hydrological modelling results. Fig. 2-28 shows the validation and comparison of models with observed data.

As could be seen in preceding paragraphs, advance warning about the incoming flood peak and its probable time of occurrence can be achieved by several models. However, selection of a particular method or model, and its accuracy for a given site is largely governed by three factors - data availability; forecaster's knowledge of, and his experience with the basin; and forecaster's familiarity with software to be used in the forecast process.

The illustrated texts mentioned in this module are just the trail of a beginning and more of the subject and in-depth precision knowledge base, the readers are suggested to refer to advanced literature layouts.

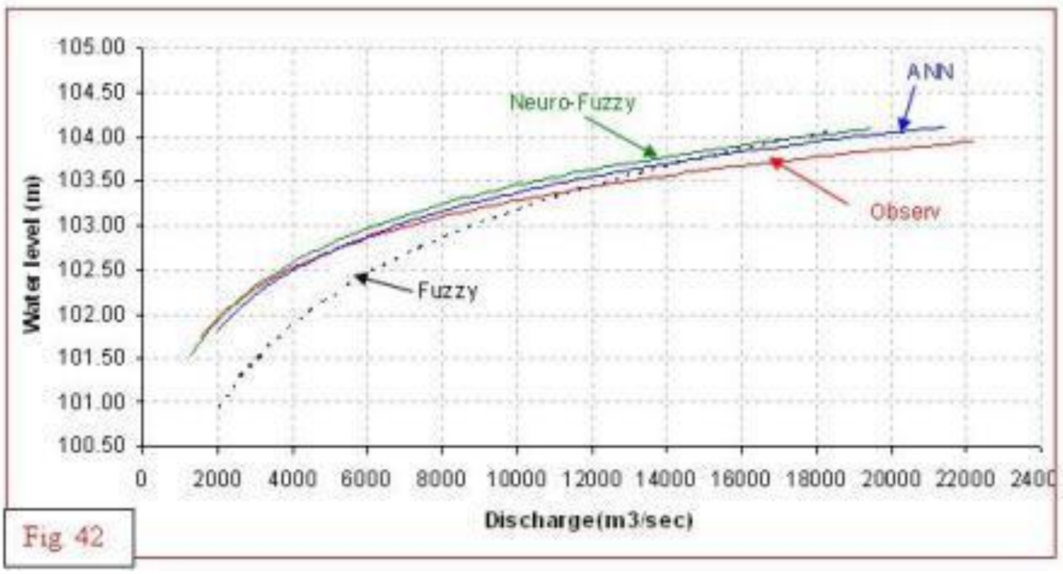


Fig. 2-28 Validation and comparison of results with observed data

2-3. Forecast updating and verification

Before verification and validation of the model, calibration process is need. Ideally the objective of calibration is to remove all possible bias and eliminate all possible noise included in the model. In reality, because of the constraint of input data quantity and quality, and simplistic assumptions that may be inherent in the model, care should be taken to achieve the proper balance between the calibration objectives and goodness-of-fit statistics. Sometimes, the latter may have to be sacrificed somewhat in order to achieve spatial consistency of the parameters. Generally, maybe there are three main objectives when calibrating conceptual hydrological models to an entire river basin for river forecasting applications. One objective that is relevant to FF techniques is when, the parameters of the models should function as they are intended: conceptual models were designed to have a physical basis and the parameters control portions of the models that represent specific components of the overall process. The effects of each parameter are designed to be reflected in specific sections of the simulated hydrograph, for example rate of rise, peaks and flood volume. To be consistent with the physical basis of a model, and to produce results that will not only best reproduce the full range of historical observations, but also be most likely to extrapolate correctly beyond what was observed in the available historical record, each parameter should be used as it was intended. This means that parameters should not be adjusted or weighted intuitively to modify the final output statistics.

In general, this means that, conditional to the choice of a specific model, its parameters will be adjusted to make the predicted values of the model resemble the observed ones. It is also important to recognize that model parameters may not fully incorporate a physical meaning, but are mostly uncertain quantities that reflect all the sources of error. In which case, parameter estimation, and consequently model calibration, loose their original meaning, and the full probability density of the parameters must be derived. Moreover, if we consider that the parameters of a physical-process model have a clear physical meaning and are marginally affected by the scale of the representation, the parameter values should not be estimated but set to reflect the a priori knowledge. The reason for this lies in the fact that parameter estimation (particularly when using least squares techniques) tends to discard the extremes in the predicted values, since the method generally aims at preserving the central moments of the observed quantities. There are two basic methods for the calibration of hydrological models:

a)The trial and error method

b)Automated parameter optimization

After calibration, the validation period used for verification should be long enough to incorporate several observed flood events, so it may need to be of two or more years extent. A number of statistical methods such as Root mean square error (RMSE), Average absolute error (AAE), Coefficient R2 and NASH-Sutcliffe coefficient and several graphical verification criteria are available to determine the success or otherwise of verification, and these can be applied to all model estimation points[3]. Comparing hydrographs provides a qualitative evaluation of the simulation skill, as the graphical representation permits a quick comparison between simulated and observed levels within a time frame. Seban and Askew (1991) categorized these errors as (i) volumetric or amplitude errors, (ii) timing or phase errors and (iii) shape errors or i and ii (Fig 2-29).

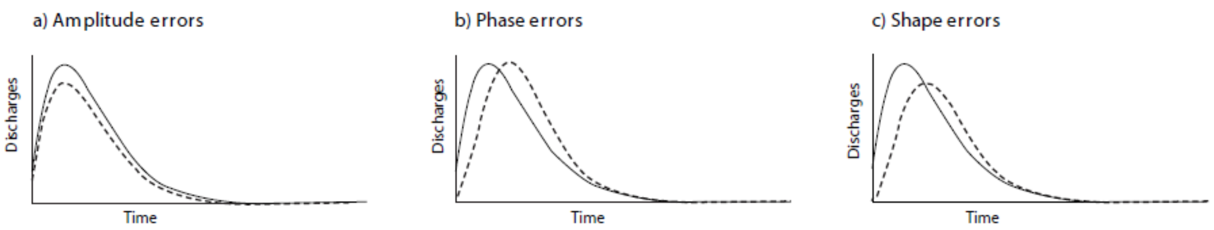


Fig. 2-29 Types of error between measured and simulated flood hydrographs

This allows useful comparisons to be made with alarm levels and forecast lead time. The accurate representation of flood volume is also important, in that it demonstrates how effective the model is at relating the rainfall and runoff responses, and with regards to flood modelling, especially for out-of-bank flows (amplitude errors). The shape characteristics of the modelled (i and ii errors) and observed floods can be tested by the following parameters that based on Root mean square error statistical method:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{Q}_i - Q_i)^2}{N}}$$

where:

i = time step;

N = total number of time steps considered;

$\hat{Q}_i$ = computed discharge at the i-th time step;

Q_i = observed discharge at the i-th time step;

a)Peak percentage difference between observed and simulated floods:

$$Q_{\max}\ [\%] = \frac{\hat{Q}_{\max} - Q_{\max}}{Q_{\max}} * 100$$

where:

$Q_{\max}$ = observed peak flow;

$\hat{Q}_{\max}$ = simulated peak flow.

b) Phase difference of the peak flow (hours):

$$\Delta t_{\max}\ [h] = \hat{t}_{\max} - t_{\max} \qquad (4.7)$$

where:

$t_{\max}$ = time (hours) at which the observed peak reaches the control section;

$\hat{t}_{\max}$ = time (hours) at which the simulated peak reaches the control section.

c) The volumetric difference:

$$\Delta V\ [\%] = \frac{\left|\hat{V} - V\right|}{V} * 100$$

where:
V = observed volume;
$\hat{V}$ = corresponding simulated volume;

For selected flood events it is also recommended to test performance by defining a water stage threshold level to compare the time and volume of both the observed and computed hydrographs above the threshold. This could be done for a proposed or existing alarm or danger level, or a flow exceedance category, for example the level exceeded by 10 per cent of the flow values.

As a mentioned above, In flood forecasting, a model with constant parameters may not be able to completely represent the complex processes in a basin. As a result, the simulated hydrograph can differ from the observed hydrograph, mainly due to uncertainties in input data, differences between basin physics and model structure, model calibration, and changes in catchment characteristic over time.

The volumetric errors are mainly attributed to inadequate model structure and basin representation, input/output data error or a combination of these errors. Timing errors may be introduced by the routing component of the model or by spatial and temporal discretization, whereas the shape errors are induced mainly in the conversion of rainfall to runoff by the model. These three types of errors can occur in different combinations in hydrologic models. Therefore, an adaptive forecast scheme may be used to update the model parameters, state variables and change in basin behaviour that cannot be simulated by the initial model (Young 2002, Mediero et al. 2012)[1].

As a result, forecast updating and data assimilation have become major components of FF. A variety of techniques for forecast updating are available with the goals of error prediction, data assimilation, and parameter updating (Sene, 2008). Forecast updating maybe periodic or real time. Updating procedures provide feedback to the hydrological simulation models by estimating errors between model output and observed state variables (Fig.2-30).

Simple updating procedures consider addition of the current error to the next new forecast for improving model outputs, compared to the observed hydrograph. More complex procedures involve analyzing the error series δY1, δY2,…,δYi to identify possible trends or periodicities that can be extrapolated to next time step to estimate the potential new error δYi+1, which are then used to update the new forecast(WMO 2012).

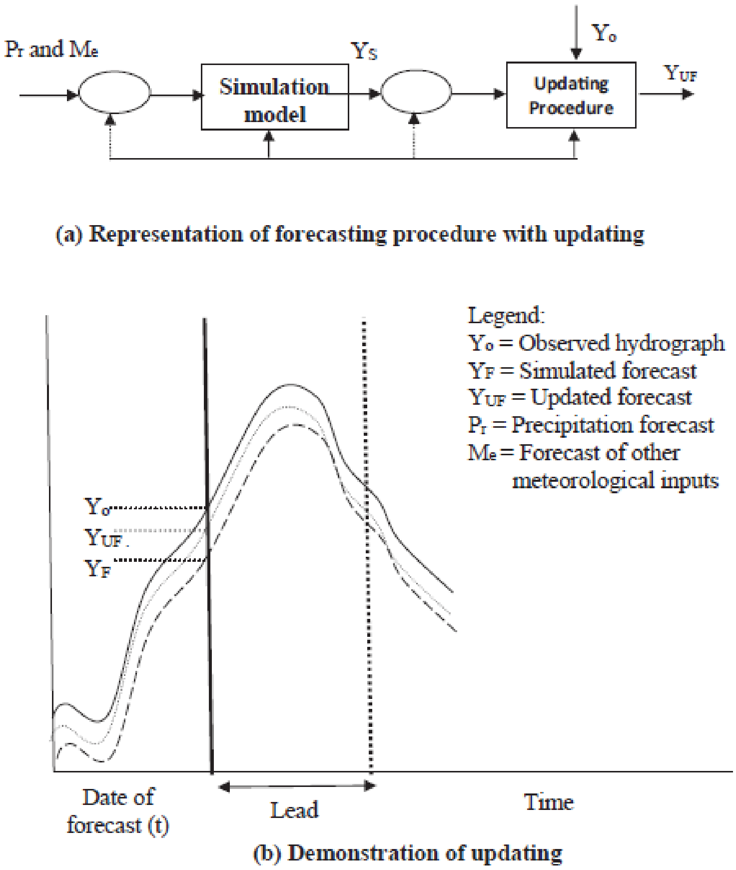


Fig.2-30 Schematic diagram of forecasting with updating (adapted from Serban and Askew 1991).

The observed values, Yo1, Yo2,..., Yoi, can be used to redefine the state variables of the forecast model. This is termed recursive estimation, and if the forecast model can be cast in a sufficiently simple form, it provides a formal strategy for adjusting model output. One example is the Kalman Filter, which is frequently used for updating an FF by employing the general algorithm:

$$\theta_j^{up} = \theta_j^s + Ke_j$$

where θ_j^{up} = the updated state at time j, θ_j^s = the simulated state at time j, K = the Kalman Filter gain, which is a function of noise statistics, and e_j = the error at time j (difference between simulated and observed output). These estimates

Model performance generally declines with increasing lead time, and thus it is generally useful to evaluate how model performance varies with lead time in order to establish the reliable lead time of a model (Sene 2008)[1].

2-3-1-Forecast verification criteria

Forecast verification is somewhat different from the model verification described above. A number of criteria exist to verify forecasts and the evaluation is used to improve models and to develop confidence in decisions made according to forecasts. selection of criteria, together with their rationale, is summarized in a document made available to the public at the Australian Bureau of Meteorology Website:

http://www.bom.gov.au/bmrc/wefor/staff/eee/verif/ verif_web_page.html.

Examples include the skill scores known as probability of detection (PoD), false alarm rate (FAR), the relative operating characteristic (ROC) and the Brier skill score. There has also been progress in evaluating the economic value of the forecasts, for example with the Relative Value (RV) score. It is recommended that the use of these techniques should become more widespread amongst flood warning practitioners, to gain a full perspective of the usefulness of hydraulic and hydrological models and to improve operational decisions.

"Continuous measures" such as bias (mean error), the root mean square error (RMSE) and the mean absolute error (MAE) all measure differences between forecast and actual quantities in numerical terms. There is no absolute measure of what constitutes a "good" or "poor" score. However, after a period of use it can be decided what ranges are acceptable for the application in question. The methods will provide a means whereby successive sets of results will indicate whether the accuracy of measures are improving or not.

In the case that forecasts relate to a threshold, either a quantity or a time, for example a flood peak forecast, then appropriate measures will be used based on the contingency table or "categorical measures" approach. These may include the hit rate (HR) or PoD, FAR (which is 1 / probability of occurrence [PoO]), and the threat score (TS) or conditional success index (CSI). These measures allow a target index to be established, whereby an ideal level of successful achievement, for example 75 per cent, could be defined in terms of numbers of hits, misses and false alarms[3].

The warning component of an FF system can also be evaluated using a threshold-based evaluation, where contingency tables are used to identify false alarms or probability of detection.

However, for all verification methods, the low frequency of high flood events, the lack of data for the high flood events, and the issues associated with verifying flood models with mean discharges significantly limits verification of flood forecasting(Cloke and Pappenberger 2009).

2-4- Data resources

2-4-1- RS and GIS

The physical characteristics of the basin (such as surface area, topography, geology, and land-surface cover) determine the nature of potential flooding. The hydrological response of a basin is impacted by changes in land use associated with urbanization, forestry, agriculture, drainage, or channel modification (Ma et al. 2009)[1]. A record of such changes over time is essential to updating FF models. Remote sensing (RS) such as satellite and radar (INSAR, Daliri,2018), generates information, sometimes in real time, on the spatial and temporal characteristics of a storm and a basin. The full potential of RS for applications related to flood forecasting can be harnessed by the integration of data from a variety of sensors operating at different wavelengths (Gangwar, 2013)[1]. Geographic Information System (GIS) provides a range of visualization products useful for FFWS, e.g. visualization of areas likely to be submerged and the movement of a flood wave (Fig.2-31).

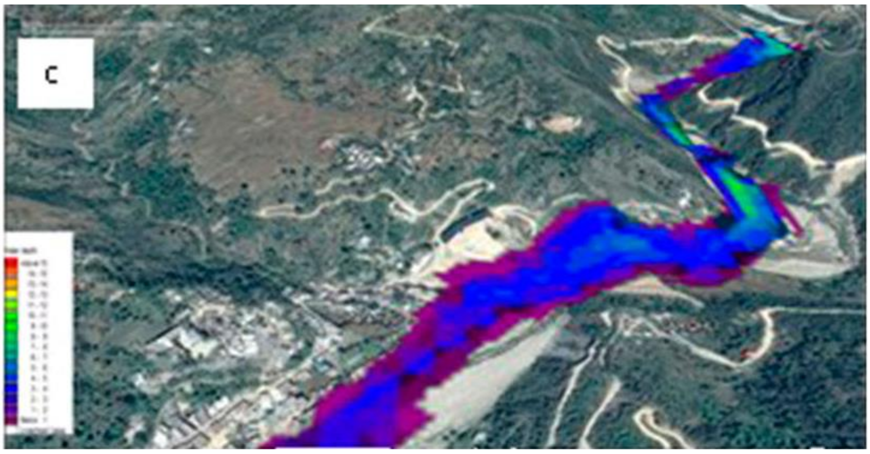


Fig.2-31 Simulated inundation mapfrom HD model[1]

Some data such as DEM, land use, snow/Ice melt data, soil moisture and water storage, precipitation measurement, flood inundation mapping and other data that mentiond above can obtain and estimate by RS techniques.

2-5- Challenges and future directions

Pagano et al. (2014)[1], describe four key challenges in operational forecast, namely:

(i) best use of available data,

(ii) modelling for accurate prediction, (especially in ungauged basins and global hydrological forecasts based on the global model and mesoscale models and nowcasting, chapter 1)

(iii) translating forecasts to effective warnings-disseminating timely information to affected community and concerned authority for taking right decision, and

(iv) administering the operational forecast – conservative approach of forecasting institutions due to perceived liability, capacity building of personals and retention of talented employee.

Significant advances are being made in remote-sensing techniques, and hydrologic modelling tools for FF need to be continuously updated to make full use of these techniques. Measurement of river flow by satellite-based sensors has the potential of overcoming problems, where such data are not available. Insufficient implementation and maintenance of ground-based, real-time hydrologic observation still remains a challenge, because it is necessary to determine the lag time between data observation and availability to help flood forecasters and reduce uncertainties and erros, so Ensembles of Numerical Weather Predictions (NWPs) and ensemble flood forecasting are being increasingly used in flood forecasting systems (Chapter 2).

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Chapter 3 Uncertainties in Flood Forecasting systems

"You cannot be certain about
uncertainty"

—Frank Knight,1972

3-1 Introduction

Model forecasts are inevitably affected by different sources of errors and uncertainties. In theory, the degree and influence of all these errors should be accounted for to obtain an unbiased minimum variance forecast. From statistical theory it is known how best to account for, and possibly eliminate, errors in forecasts. Following the statistical approach, each error source should be described through its probability density function and marginalized from the predictive probability. Unfortunately, most of the relevant probability densities are not only unknown but also extremely difficult to infer. Even the choice of model has a degree of error involved[3].

Flood event probability is of great interest, both in estimating flood risk and in decision making about design of structures for flood protection. Basic uncertainties to flood event estimation classification is on natural and epistemic uncertainties. Concretely, hydrological, hydraulic, statistical and geotechnical uncertainties play role in real value of flood event probability, each of these having two basic concepts of uncertainties involved in it. Climate change and global warming could play significant role in future floods, bringing more uncertainty in statistical description and hydrological processes of water protection systems.

In decision making about hydraulic structures, that is, flood protection structures, for given solutions of the problem, usually the range of different scenarios and their risk is analyzed. It is quite difficult to say what is really going to happen, and decision makers can only make decisions under uncertainty, knowing only the probabilities and the range of reliability for each possible state of flood protection system.

Some uncertainties can be quantified, some cannot. Rational use of the term uncertainty includes the quantification of those[6]. When it is about flood protection structures, the absence of absolutely safe system is the valuable thing to have in mind. So, there always exists dealing with the event causing possible damages, and rational deliberation about it includes defining its probability p within the given range of uncertainty, that is, $p \pm \Delta p$. [6].

The uncertainties included in water resources management can be distinguished in data uncertainties, model uncertainties and technological uncertainties. Data uncertainty is usually said to be the main uncertainty driver and the greatest part of the uncertainty influencing the flood probability estimation.[5] Considering the relatively young hydrological history of, depending of the area, 50-100 years in estimating the events with several times greater return periods, it seems quite convenient to corroborate previous sentence. [5]. Not that just hydrological history is relatively young and not filled with longer period of measurements, but various imperfections in measurings, errors done by humans, irregularly calibrated or poorly maintained equipment, inadequate sampling etc. also contributes to the amount of uncertainties.

Though models are just simplified representation of complex systems and always have some aspect of uncertainty involved whether through describing the system or through calibration, validation or wrong interpretation of system's nature. [6]

Merz and Thieken (2005)[5] separate natural (inherent, intrinsic) and epistemic uncertainty in the flood frequency analysis. Epistemic uncertainty arises from lack of understanding, measuring and describing the system, its phenomenons and bonds between inputs and outputs.[5] The main flood initiator, without which floods in fact can not occur, are rainfalls and snow melting. As these phenomenons have numerous cause-consequence connections with the whole sequence of different processes in atmosphere, the use of stochastics becomes unavoidable the probabilistic analysis of floods. It is hard, not to say impossible, to engage all of the factors influencing the formation of a flood event. Previously mentioned cause-consequence connections also include the part belonging to the natural uncertainty. Additionally, possible unexpected damages on levees, dams, lack of design and monitoring, increase the epistemic uncertainty making the modeling of probability and reliability of flood structures more challenging. The epistemic uncertainty can be reduced.[5] Natural uncertainty arises from variability of natural phenomenons. Basically, they are induced by climatic, atmospheric, hydrological variations, but also by unconsistencies in levee and foundation ground properties. Principally, the natural uncertainty can not be reduced.[5] In the way of controlling the material properties and choosing the certain places for material excavation, the aspect of unconsitence of building material can be partially bypassed.

Ranzi et al. (2012) include climate change as category of uncertainty beside hydrological, hydraulic, geotechnical and climate change [6]. In the paper the classification of uncertainties which is used is division into statistical, geotechnical, hydraulic and hydrological uncertainty, as they seem to be obvious categories influencing the estimation of high water event probability, but up with having in mind climate variations could influence every of those. The objective of the chapter 2 is to notice, describe and classify those uncertainties and their components, and give recommendations about their treatment. The importance of given matter reflects in the risk assessment, highly determined by probability of set of scenarios, and designing the flood protection structures, where uncertainties, that is hydrological events with its reliability, should be indicated.

The increased availability and application of probabilistic weather forecasts in flood forecasting means that the uncertainty arising from the precipitation forecast can be assessed. This has led to a wider interest in how uncertainty is affecting flood forecast systems. In literature there are general techniques and principles available on how to deal with uncertainty. However, there are no of well-accepted guidelines on the implementation these principles and techniques. There is neither coherent terminology nor a systematic approach which means that it is difficult and perhaps even impossible to assess the characteristics and limitations of uncertainty quantification methods. Selecting the most appropriate method to match a specific flood forecasting system is therefore a challenge. The main findings of this review are that there are remaining mathematical and theoretical challenges in uncertainty quantification methods and that this leads to the use of assumptions which in turn could lead to a misrepresentation of the predictive uncertainty.

Historically, many flood forecasting systems produced deterministic forecasts. Ensembles of Numerical Weather Predictions (NWPs) are being increasingly used in flood forecasting systems. This allows the uncertainty of the meteorological forecast input data to be assessed, examples of this development include The Hydrological Ensemble Prediction Experiment (HEPEX, 2017) initiative (Cloke and Pappenberger, 2009)[4,1]. Recently, there has been more emphasis on the presence of uncertainty in all components of the forecasting system (Krzysztofowicz, 2002; Pappenberger et al., 2005)[4,1]. Research with end-users has found that there is an appetite for uncertainty information if improvements in accuracy and lead time can be achieved (Lumbroso et al., 2009)[4]. Powerful techniques are becoming more widely available within flood forecasting systems and these allow the quantification of uncertainty, sensitivity analysis, risk analysis and decision analysis[4,1]. However, there are no of guidelines on how to implement these principles and techniques in complex flood forecasting systems where there are multiple sources of uncertainty to consider (Zappa et al., 2010; Liu and Gupta, 2007)[4]. There is a lack of coherent terminology and systematic approaches which leads to difficulty in assessing characteristics and limitations of individual methods. This makes selecting the most appropriate method for practical problems difficult and perhaps impossible (Montanari, 2007)[4]. Within flood forecasting systems Liu and Gupta (2007) highlight four areas that need to be addressed[4]:

I. Understanding of uncertainty (this chater)
II. Quantifying uncertainty (this chapter and other chapters)
III. Reducing uncertainty (calibration, updating:,…chapter 2 and other chapters)
IV. Communication of uncertainty. (warning dissemination: charter2 and this chapter)

This chapter focusses on areas one and two: the understanding and quantification of uncertainty. More explicitly, the aim of this chapter is to provide a review of the understanding of uncertainty in flood forecasting systems and the available methods of dealing with it. Further, this chapter identifies gaps and limitations with regards to the understanding and quantification of uncertainty.

3-2 Concept of uncertainty

There are some things that you know to be true, and others that you know to be false; yet, despite this extensive knowledge that you have, there remain many things whose truth or falsity is not known to you. We say that you are uncertain about them. You are uncertain, to varying degrees, about everything in the future; much of the past is hidden from you; and there is a lot of the present about which you do not have full information. Uncertainty is everywhere and you cannot escape from it (Dennis Lindley, (2006)). So, Uncertainty, the lack of certainty, a state of limited knowledge where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome. Uncertainty refers to epistemic situations involving imperfect or unknown information. It applies to predictions of future events, to physical measurements that are already made, or to the unknown. Uncertainty arises in partially observable and/or stochastic environments, as well as due to ignorance, indolence, or both.

Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated.... The essential fact is that 'risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all. Frank, K. (1885–1972).

Measurement of uncertainty (measured value ± uncertainty **)**

A set of possible states or outcomes where probabilities are assigned to each possible state or outcome – this also includes the application of a probability density function (PDF) to continuous variables.

Second order uncertainty

In statistics and economics, second-order uncertainty is represented in probability density functions over (first-order) probabilities.

Risk

A state of uncertainty where some possible outcomes have an undesired effect or significant loss.

Measurement of risk

A set of measured uncertainties where some possible outcomes are losses, and the magnitudes of those losses – this also includes loss functions over continuous variables.

Other taxonomies of uncertainties and decisions include a broader sense of uncertainty and how it should be approached from an ethics perspective:[8]

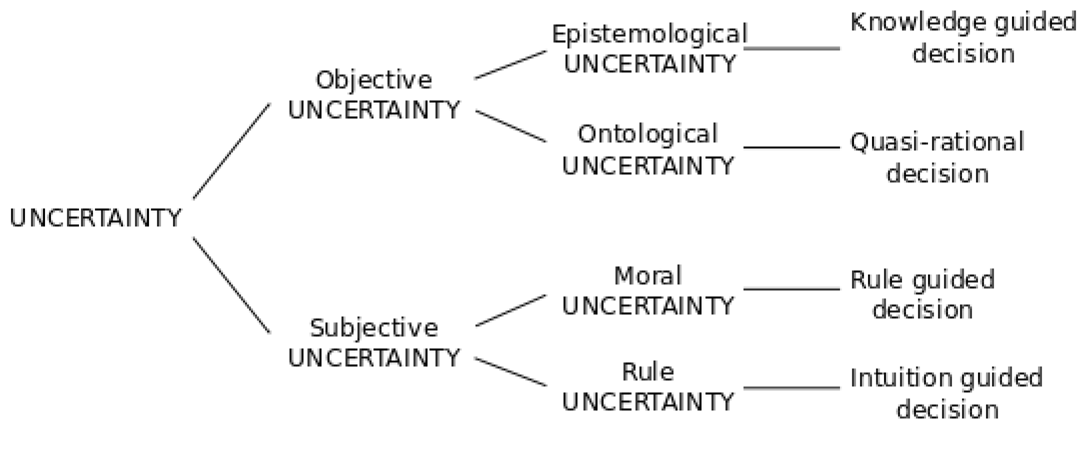

Fig. 3-1 A taxonomy of uncertainty[8]

For example, if it is unknown whether or not it will rain tomorrow, then there is a state of uncertainty. If probabilities are applied to the possible outcomes using weather forecasts or even just a calibrated probability assessment, the uncertainty has been quantified. Suppose it is quantified as a 90% chance of sunshine. If there is a major, costly, outdoor event planned for tomorrow then there is a risk since there is a 10% chance of rain, and rain would be undesirable. Furthermore, if this is a business event and $100,000 would be lost if it rains, then the risk has been quantified (a 10% chance of losing $100,000). These situations can be made even more realistic by quantifying light rain vs. heavy rain, the cost of delays vs. outright cancellation, etc.

Some may represent the risk in this example as the "expected opportunity loss" (EOL) or the chance of the loss multiplied by the amount of the loss (10% × $100,000 = $10,000). That is useful if the organizer of the event is "risk neutral", which most people are not. Most would be willing to pay a premium to avoid the loss. An insurance company, for example, would compute an EOL as a minimum for any insurance coverage, then add onto that other operating costs and profit. Since many people are willing to buy insurance for many reasons, then clearly the EOL alone is not the perceived value of avoiding the risk[1].

Some also create new terms without substantially changing the definitions of uncertainty or risk such as , surprisal, Vagueness and Ambiguity. Daliri (2014) develop concept of Vagueness in groundwater safe yield [1].

surprisal is a variation on uncertainty sometimes used in information theory or one huge extreme event in water resources components.

Vagueness is a form of uncertainty where the analyst is unable to clearly differentiate between two different classes, such as 'person of average height.' and 'tall person'. This form of vagueness can be modelled by some variation on Zadeh's fuzzy logic or subjective logic.

Ambiguity is a form of uncertainty where even the possible outcomes have unclear meanings and interpretations. The statement "He returns from the bank" is ambiguous because its interpretation depends on whether the word 'bank' is meant as "the side of a river" or "a financial institution". Ambiguity typically arises in situations where multiple analysts or observers have different interpretations of the same statements.

Uncertainty may be a consequence of a lack of knowledge of obtainable facts. That is, there may be uncertainty about whether a new rocket design will work, but this uncertainty can be removed with further analysis and experimentation.

At the subatomic level, uncertainty may be a fundamental and unavoidable property of the universe. In quantum mechanics, the Heisenberg uncertainty principle puts limits on how much an observer can ever know about the position and velocity of a particle. This may not just be ignorance of potentially obtainable facts but that there is no fact to be found. There is some controversy in physics as to whether such uncertainty is an irreducible property of nature or if there are "hidden variables" that would describe the state of a particle even more exactly than Heisenberg's uncertainty principle allows. Although A.Einstein, believe there is no uncertainty in real world.

Uncertainty of a measurement can be determined by repeating a measurement to arrive at an estimate of the standard deviation of the values. Then, any single value has an uncertainty equal to the standard deviation. However, if the values are averaged, then the mean measurement value has a much smaller uncertainty, equal to the standard error of the mean, which is the standard deviation divided by the square root of the number of measurements. This procedure neglects systematic errors, however.

When the uncertainty represents the standard error of the measurement, then about 68.3% of the time, the true value of the measured quantity falls within the stated uncertainty range. These values follow from the properties of the normal distribution, and they apply only if the measurement process produces normally distributed errors. In that case, the quoted standard errors are easily converted to 68.3% ("one sigma"), 95.4% ("two sigma"), or 99.7% ("three sigma") confidence intervals.

Measurement is a process of experimentally obtaining the value of a quantity. The quantity that we intend to measure is called measurand. In principle, the aim of a measurement is to obtain the true value of the measurand. Every effort is made to optimize the measurement procedure in such a way that the measured value is as close as possible to the true value. However, our measurement result will be just an estimate of the true value and the actual true value will (almost) always remain unknown to us. Therefore, we cannot know exactly how near our measured value is to the true value – our estimate always has some uncertainty associated with it. The difference between the measured value and the true value is called **error.** Error can have either positive or negative sign. Error can be regarded as being composed of two parts – **random error** and **systematic error** – [1]. Like the true value, also the error is not known to us. Therefore it cannot be used in practice for characterizing the quality of our measurement result – its agreement with the true value Fig.3-2).

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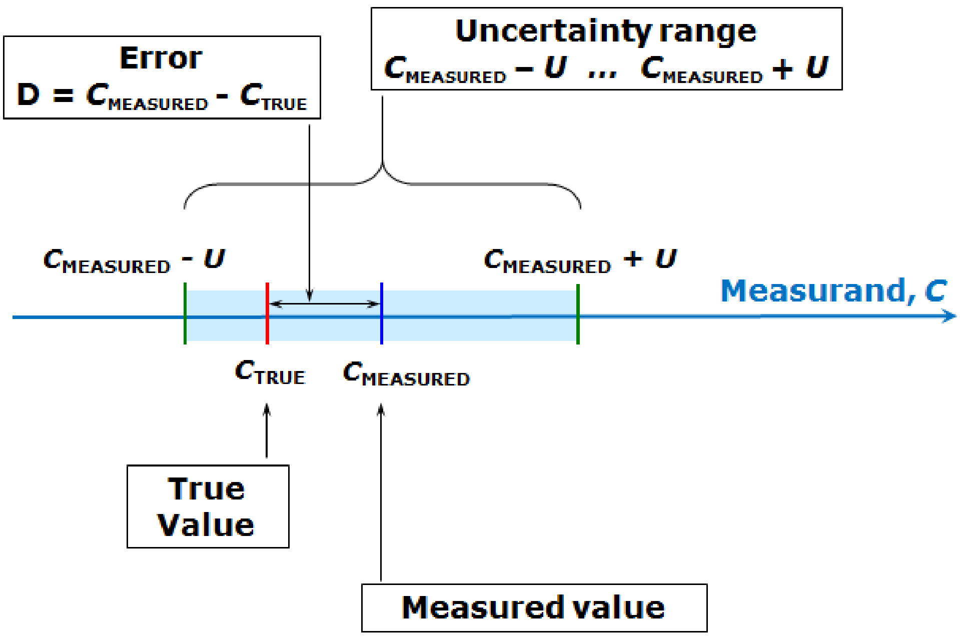

Fig 3-2 Interrelations between the concepts true value, measured value, error and uncertainty

The quality of the measurement result, its **accuracy**, is characterized by **measurement uncertainty** (or simply **uncertainty**), which defines an interval around the measured value $C_{MEASURED}$, where the true value C_{TRUE} lies with some probability. The measurement uncertainty U itself is the half-width (if is normal distributed, if not the, range is non-symmetric) of that interval and is always non-negative.

Measurement uncertainty is always associated with some probability – and it is usually not possible to define the uncertainty interval in such a way that the true value lies within it with 100% probability. Measurement uncertainty, as expressed here, is in some context also called the **absolute measurement uncertainty**. This means that the measurement uncertainty is expressed in the same units as the measurand. Also, it is sometimes more useful to express measurement uncertainty as **relative measurement uncertainty**, which is the ratio of the absolute uncertainty *U*abs and the measured value *y*:

$$U_{\text{rel}} = \frac{U_{\text{abs}}}{y}$$

Relative uncertainty is a unitless quantity, which sometimes is also expressed as per cent.

Measurement uncertainty is different from error in that it does not express a difference between two values and it does not have a sign. Therefore it cannot be used for correcting the measurement result and cannot be regarded as an estimate of the error because the error has a sign. Instead measurement uncertainty can be regarded as our estimate, what is the highest probable absolute difference between the measured value and the true value. With high probability the difference between the measured value and the true value is in fact lower than the measurement uncertainty. However, there is a low probability that this difference can be higher than the measurement uncertainty.

Both the true value and error (random and systematic) are abstract concepts. Their exact values cannot be determined. However, these concepts are nevertheless useful, because their estimates can be determined and are highly useful. In fact, as said above, our measured value is an estimate of the true value.

A FFWS may have two types of prediction failures:

a) the system may fail to issue a warning for a flood event (error of omission), and

b) it may issue a warning for an event that does not materialize (error of commission).

In the first case, there may be loss of life, infrastructure, and property due to a flood. In the second case, people may lose trust in the forecast and may not respond to the next warning. Thus, analysis and communication of FF errors and uncertainties are critical to minimize the possibilities of either type of failure[2].

Moreover While distributed models are generally expected to reproduce the hydrological processes in spatially-varied catchments more accurately, uncertainty in model parameters can lead to substantial errors in distributed models (Carpenter and Georgakakos 2006). Uncertainty indicates that something is not able to be relied on, is not known or not definite (Oxford English Dictionary, 2017). Two well-known types of uncertainty are:

aleatory and epistemic. Aleatory uncertainty is uncertainty resulting from natural variability and randomness and epistemic uncertainty is uncertainty due to lack of knowledge (Li, Chen and Feng, 2013) and [1].

In flood forecasting systems uncertainty can be referred to in terms of 'predictive uncertainty' or 'predicting the uncertainty', (Todini, 2008; Weerts, Winsemius and Verkade, 2011; Palmer, 2000; Van Steenbergen and Willems, 2015; Zappa et al., 2011), which is defined by Todini, (2008) as "the probability of any future (real) value, conditional upon all the knowledge and information, available up to the present."[4].

3-2-1 Statistical uncertainty

Statistical uncertainties can be classified in parameter and distribution uncertainty:

the first one arising from:

-unsuficient amount of data,

-type of data (peak flow with different volume or/and duration),

- data shortage,

-inappropriate method of parameter estimation,

-human and equipment errors, and… ect,.

and the second one arising from:

- the choice of distribution type for fitting the data for example

- suprisal events (corresponding with min or max in extreme conditions)

-method of calculation and …ect,.

Also, global warming and climate change and variable can affect here. So natural and epistemic unsertainties can be classified in statistical uncertainties analysis.

As the usual type of statistical analysis in design flood is univariate statistics (peak flow only) because of its simplicity and practicability, but it may be analysis with two or more variables (peak flow pay attention to volume and duration of flood) under circumestance that mentioned in continue.

Statistical methods in hydrology, as usual, can be applied if the following conditions are satisfied: sequence is made from random variables, variables are mutually independent, sequence is homogenous, stationary and long enough. In flood frequency analysis there are two different approaches that are used for estimating the probability of flood event, that is, return period – annual maximum approach (AMA) and threshold exceedance approach (TEA). In AMA hydrological data is taken in the measuring period of at least 30 years and for every year peak flows are taken into statistical analysis. Therefore, the return period T(Q), in years, of the certain value of flow Q is calculated as follows[1]:

$$T(Q) = \frac{1}{P(q \geq Q)}$$

where P(q ≥ Q) is the probability of exceedance of the flow Q.

In TEA, flows with values above the certain threshold are taken in the analysis. It is usually applied in the circumstances in the cases when available data is taken form the measuring period less than 30 years (data shortage). The return period is calculated as follows:

$$T(Q) = \frac{N}{M}\frac{1}{P(q \geq Q)^*}$$

$$P(q \geq Q)^* = \frac{N}{M}P(q \geq Q)$$

where P(q ≥ Q) * is the probability of exceedance of the flow Q calculated using the total number of sequence members, N is the number of unit time intervals and M is the number of sequence members.

Using the AMA approach, theoretically could lead to choosing the flows close enough that some kind of natural dependence between those could be involved, but this is the possibility that rarely happens. Having in mind the year is quite rigid time border, the possibility of appearance of two timely closed high water waves connected with the same atmospheric event, one at the end of the year, one at the beginning of the next year, exists yet. In TEA, due to the usage of threshold, there is reasonable chance to have two or three mutually dependent events and while selecting the threshold, one high enough which excludes dependence should be chosen. Beside taken assumption of numerous causes influencing the flow in rivers, high water events are usually the consequence of the prevailing of rainfall event or snow melting in the certain period in the relation to other causes. So in both methods, as the high water events are mainly driven by one cause, there is a question of homogeneity involved in analysis. Although events could have similar and greatest peaks in analysis, the nature of high water event including its volume and duration is of interest. Still, flood structures dimensions and the intensity of the flood, is driven by those two parameters and the greatest peak does not necessarily has the greatest volume (in “very” small duration). Thus, in the manner of avoiding the previously said, statistical analysis can be made in events observing way, calculating the probability and return period for every certain high water event important with its significance. Also, using AMA in this situation does not put the interesting event on the end of every year, which tends to have large magnitude, especially looking the volume of water (the area under the flow) in December (1982). Although the mentioned event is not the greatest of all events, it does not mean that sometimes in next years this event can not exceed all the other events in the sense of volume, no matter as high water event is not observed in measurements (Fig 3-3).

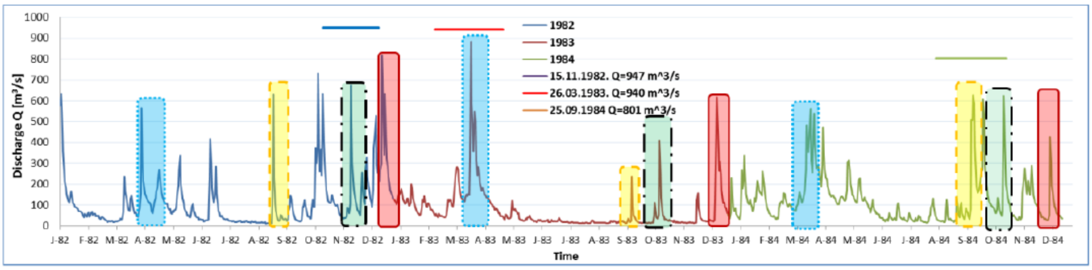

Fig 3-3 Hydrograph of Brodarci station for years 1982-1984[5]

It is implicitly understood that all events (elements) in space V must be mutually exclusive, equally distributed in space and deplete the space as much as possible. The way the second and third property are fulfilled is made through using the hydrological measurements on disposition. Moreover, without timely longer observations these properties can hardly be improved. As Hrelja (2007)[5] stated that is supposed to have in mind the relatively young history of systematically taken hydrological measurements. In that manner, even if the one certain type of hydrological event is taken, the real space Ω of naturally existing elements representing the same type of event, including those of smaller and those of higher magnitudes, is hardly known, and thus depleted. Analyzing the high water events and predicting those with great return periods (of 100, 1 000, 10 000 years) requires approximation of event distribution using some of the famous distributions (Gauss, Weibull, Pearson, Gamma, Galton and so on) and extrapolation beyond really taken measurements[1].

The epistemic uncertainty, arises from defining the appropriate statistical approach to treat high water events. Moreover, analysis should include all events considered as high water events. As volume and duration of the event, beside the flow, are also of the great importance, they have to be included in analysis. So the way these could be avoided is in observing the similar events in some specified time increments which will conduct to situation where the probability and return period for every different event could be estimated. Then, by using the **Bayesian** approach, probability that any of the events will happen could be estimated. On the other side, no matter all of this is fulfilled and the approach is perfect, from short period of measurements it is impossible to get the full information about any event.

Natural uncertainty arises from the fact that statistical distribution of various hydrological events is susceptible to changes, due to reasons like climate variations, but also due to possible changes in river and basin environment. Thus, the sequence homogeneity and stationarity could be influenced through this type of uncertainty. Possible climate changes and global warming could affect this type of uncertainty. One of the definitions of climate changes says that they influence the statistical distribution of hydrological events. The open question is will it affect the nature of high water events and floods.

Flood damages tends to be higher, but the main reason lies in fact that material resources in the vicinity of flood protection structures, tends to value more.[5] Due to the last IPCC synthesis report, increasing of the extreme rainfalls and river flows influence intensity and occurrence of floods in regional level, not in global level (IPCC).[5] So, with the temperature increasing the way it goes like today, it is quite possible to have changes in probability of high water events.

3-2-2 Geotechnical uncertainty (levee or earthen dam)

Flood event connected with geotechnical uncertainty has dual nature. As the first, flood can occur due to undersizing of the structure (levee or earthen dam) and thus the mechanisms which could potentiate the failure are overtopping, erosion by waves, mechanisms interconnected with seepage like piping, hydraulic failure and liquefaction. It is obvious these mechanisms also depend of the nature of high water events. Overtopping intensity depend of the duration of some high enough water level, as also seepage cannot occur without long enough duration needed for water to get through levee. Referring to the 3-2-1, these also confirms the importance of the information about duration of the high water event, not just the peak flow. As the second, flood can occur due to the insufficiently robust structure which can be caused by various damages on the levee, including the occurrence of sliding surface, subsidence, damages caused by previous events etc. Geotechnical uncertainty cannot be strictly separated from hydraulic uncertainty because, that is, uncertainty arises from occurrence of hydraulic phenomenons, but also depends on material properties. Thus, failure mechanisms include[5]:

- Sliding surface on the upstream slope or on the the downstream slope
- Overtopping
- Piping through levee or ground
- Hydraulic failure of the outside slope or ground
- Ground and levee material liquefaction
- Erosion by waves
- Ground and/or levee subsidence
- Earthquake
- Different type of damages on levee caused by animals and/or humans, tree damages etc...

As it is obvious, except of material properties, occurrence of these mechanisms depends of the high water nature – intensity of water level increase, decrease and duration. These mechanisms are principally acting in the combination and levee failure due to breaching is complex for full physical and mathematical treatment[1]. Mathematical models usually, as the output result, give the time failure and output hydrograph. This also implies that any estimation of levee failure probabilities is, in the least, challenging.

Occurrence of sliding surface could potentiate the levee failure and thus the occurrence of flood event, if not at the moment of some present, possibly in some of the future high water events. This stands because the most critical situation for slides to occur (also surface slough) is when water level decreases suddenly. Then slopes, saturated with water and additionally loaded with flow from saturated area, have the greatest magnitude of load and the lowest resistance. For calculation of the sliding occurrence probability P(s), both on upstream and downstream slope, the concept of reliability from construction engineering can be used as it is in:

$$P(s) = 1 - \Phi(\beta)$$

where $\Phi(\beta)$ is is the cumulative probability function for the safety index β calculated using the equation:

$$\beta = \frac{ln(\frac{C_{50}}{D_{50}})}{\sqrt{\sigma^2(lnc) + \sigma^2(lnD)}}$$

C50 and D50 are the median values of the capacity and demand. Capacity is given as the density distribution function of material resistance and demand as the density distribution function of loads acting on levee slope. Label σ stands for the standard deviation of capacity and demand given in lognormal distribution. Full treatment of these mechanisms includes considering the nature of water level decrease, which also emphisize the importance of considering the volume and duration of high water events. So the approximate probability of failure and flooding involves using two above equations, in combination with:

$$P(O) = 1 - (1 - \frac{1}{T})^{LT}$$

having in mind that, due to water level decrease, it is not necessary this triggers the flooding.

Overtopping occurs if water level exceeds the level of levee crown. As the circumstances where, at the same time, there are no any geometrical imperfections of levee and the material is appropriately compacted, it is quite possible that overtopping will potentiate the levee failure. Principally, the levee crown elevation is estimated as the sum of the level of the high water event with certain probability (that is return period) and some value called freeboard. Ignoring the freeboard, the overtopping probability P(O) (sometimes also called risk) of the high water with certain return period T during the structure life time LT can estimate by the above equation.

In the cases when during the high water, due to the seepage through levee or ground, water flow removes material particles creating thin channels, the process is called piping. Further increasing of particles removal will enlarge those channels initiating the breaching of the levee. As mathematical models of internal erosions are still developing, probability quantification of levee failure due to piping is done by subjective judgement, so called subjective probabilities. The probability of breaching by (through) piping P(Btp) can be estimated using the University of New South Wales method or modified form like in:

$$P(B_{tp}) = \prod_{i} w_i P_{ref}$$

where wi are the weights, i characteristics affecting the performance, Pref probability of breaching by piping of a reference levee with fixed characteristics. Characteristics include anything which could contribute to piping, like animal burrowing, seepage, subsidence, compactness, existing culverts etc. depending also of the material used for building levees. The same way probabilities of different damages can be estimated, which is already included in the mentioned method.

Levees are usually designed and built in the way the compactness is as high as liquefaction should not occur during the high water event. Ground made of loose material, like sands, could potentiate fluidization, and flow of water coupled with material due to the pressure of water on upstream side could cause the levee failure and very likely the flood event. Although the material fluidization can occur without earthquake, at least as cold flow (creep), still, liquefaction is usually analyzed coupled with trigger like earthquake. As the concrete formulation of levee failure probabilities are not found, soil liquefaction probability could be estimated due to.

Earthquakes are usually given with return period and its magnitude, and levees are sized in the manner they have got the certain safety factor, that is safety index as it is in above. The earthquake probability of the certain return period can be calculated using equation P(O), combining with equation P(s) and β and calculating the probability of the high water level of certain period resulting in the probability of concomitant earthquake with levee failure and flooding.

All of the accounted uncertainties are sometimes included in considering the probability of levee failure, without analyzing every each of those. The probability of failure is then estimated depending of the levee condition, which is roughly poor, medium or good and usually described using the levee fragility curves. The probability of failure is then given as the function of water level as it can be found in [12].

Epistemic uncertainty arises from the possibility to understand and describe all of these complex mechanisms, which usually come in combinations. Natural uncertainty arises from the range of differences in material properties used for building levees and from the nature of high water events. Realization of mentioned mechanisms does not necessarily mean the occurrence of flood event, but as they can always potentiate it, it is worth to notify them, estimate their magnitude and include them in the risk scenarios. Since the mechanisms could come individually or in combination, the effort could be made in estimating the tree event [12], resulting in the probability of all possible events.

3-2-3 Hydraulic and hydrological uncertainty

As hydraulic uncertainties cannot be separated by geotechnical, and hydrological uncertainties are also connected with statistical treatment of hydrological events, there also exist some aspects which can be precieved as purely hydraulic and hydrological. Water level and flow depend on the nature of incoming high water waves, thus consumption curve (water level dependency of flow at certain hydrological station) tend to have varying nature, creating a loop around mean value. As velocity and flow of incoming increasing water wave increase results in greater flow for the same level, outcoming decreasing wave causes less flows for the same level [1]. Thus, this part arises from the quality of hydrological measurements and, equipment and their usage, appropriate interpretation of the data, appropriate regression analysis, which are hydrological, moreover epistemic uncertainty. As natural part, hydrological processes are interconnected with climate and atmospheric processes. Climate variations and changes could make the impact on the occurrence and intensity of future floods, which is already mentioned in the chapter. Another epistemic uncertainty is thus modeling uncertainty and the question of equality of the water level return period and flow return period . That is, after the assumed levee's route and profile, it is necessary to simulate situation using the hydrograph of high water event and consumption curve of some upstream profile. The resulting water levels depends of bed roughness and geometry, as two main drivers of return period enaquality. Thus it is necessary to make calibration and validation, usually with lower return period flows, respectively with measurements on disposition, so these difficulties are hardly avoidable. Epistemic uncertainty arises from the possibility to fully understand and describe the flow in river beds, reservoirs, seepage etc. This also relates with the description of the flow coupled with geotechnical failures. Natural uncertainty arises from the range of differencies in material properties, that is, natural material used for building levees and material of the ground. Variations in materials also mean variations in hydraulic properties. Hydrological processes are interconnected with climate and atmospheric processes. Climate variations and changes could make the impact on the occurrence and intensity of future floods, which is already mentioned in the chapter.

Another epistemic uncertainty in flood estimation, is effect of sediment on the peak debit. We can modify this effect by hydraulic coefficients based on field measurements [1].

Hydrological and hydraulic uncertainty should be treated in the way of defining the reliability of the equality of flow and water level return period or find causes of this anomaly.

3-3 Sources of errors and uncertainties

Uncertainties arise in FF due to a number of sources: input data uncertainty, model uncertainty, and model parameter uncertainty. Leahy et al. (2007)[2] have characterized the uncertainties in the flood warning process and identified the various sources of errors (Fig. 3-4), and Sene (2008) has outlined the general approaches for evaluating uncertainties.

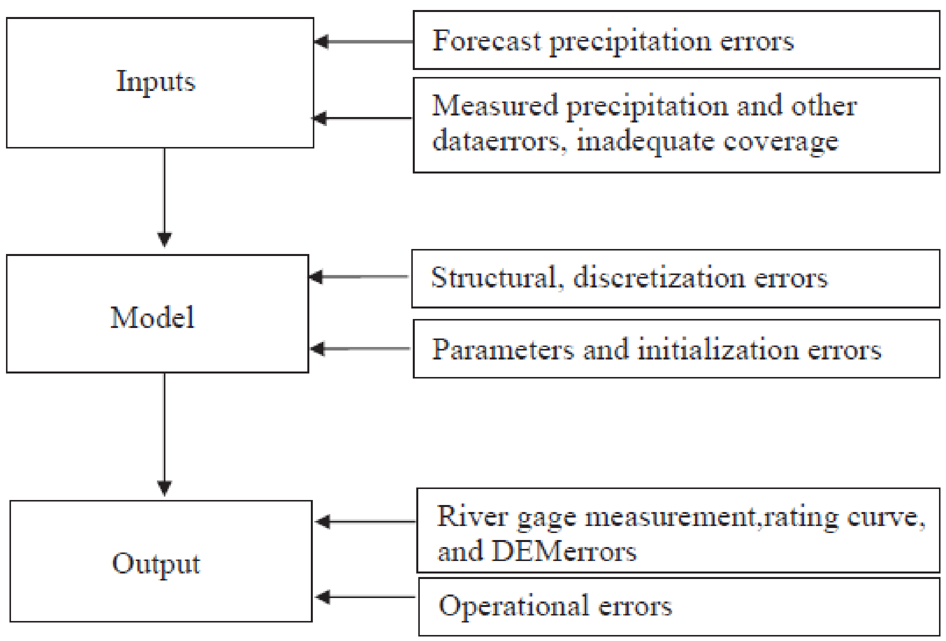

Fig 3-4 Error framework for rainfall-runoff models for example in flood forecasting[2]

The critical meteorological input in FF is observed and/or forecasted precipitation (Krzysztofowicz 1999, Marty et al. 2013)[2]. Forecasted precipitation is typically derived from quantitative precipitation forecasts (QPF) by numerical weather prediction (NWP). The grid size of NWP can be a major source of error in rainfall forecast, which is further aggravated by the positional error of these grids. Even observed precipitation can have significant uncertainties. Rain gauges sample a very small area and there can be large gaps between them, which can translate into large precipitation errors, particularly in mountainous areas (Stanton et al. 2016)[2]. Weather radars can sample large areas but do not directly measure rainfall and there are issues with conversion from reflectivity to rainfall (Catchlove et al. 2005)[2]. Flood producing storm events typically occur at highly localized scales (<10 km^2) and may not be captured by gridded remotely sensed products, such as TRMM (Stanton et al. 2016)[2]. In addition to precipitation, a number of other errors and uncertainties can be substantial. For example, errors associated with the initial conditions (e.g. soil moisture) are particularly important when the models are applied to isolated storm events. In addition, any model updating or downscaling can create errors and uncertainties, as can infrastructure operations (Cloke and Pappenberger 2009)[2]. Errors can be introduced with the use of rating curves. Flood forecasts are generally given in the form of level (gauge data), while the hydrological models typically compute discharge. A rating curve is used to transform calculated flows to water levels. Generally, rating curves are developed with a limited number of discharge observations that may not cover extreme flood events, giving sufficient room for uncertainty. In addition, there can also be uncertainties in the gauge observations. Furthermore, operational uncertainty of a FFWS can be caused by erroneous or missing data, human processing errors, or unpredictable interventions (Krzysztofowicz 1999)[2].

Finally, important errors can arise from issues with the structure of RR models misrepresenting hydrologic processes, characterized by: model structure errors, parameter errors, and spatial discretization errors. Model structure results from the decomposition of complex physics of catchments into models of physical processes. These structure errors are not resolved with more data[2]. There may also be significant uncertainty relating to model parameters, which tends to decrease with time as more recorded runoff data become available and is used to tune the model parameters. Parameter uncertainties tend to vary with the size of study area, variabilities in its properties, the number of sub-divisions of the area, and resolution of data. A third primary error associated with RR models is the spatial representation of the catchment, of which there are three common approaches:

Rectangular grids (e.g. the SHE model), sub-catchments, and response units (e.g. the SWAT model). So sources of uncertainty in a flood forecasting system are linked to the elements that are included in the chain of models and will vary for different forecast setups. For example, the inclusion of a hydraulic model to estimate the levels and extent of flooding would add additional sources of uncertainty to a forecasting system which are only relevant if this element is part of the model chain. Krysztofowicz (1999)[4] identifies input uncertainty and all other uncertainties in the aggregate (e.g. hydrological uncertainty). Table 3-1 shows the varying sources of uncertainty that can affect a flood forecasting system.

Table 3-1: Varying sources of uncertainty that can affect a flood forecasting system[4]

Sources of uncertainty according to (Pappenberger *et al.*, 2005)	**Sources of uncertainty according to** (Cloke and Pappenberger, 2009)	**Sources of uncertainty according to** (Zappa *et al.*, 2011)	**Sources of uncertainty according to** (Klein *et al.*, 2016)
Rainfall forecast	Correction and downscaling	Forecast data	NWP
Runoff model	Spatial and temporal owing to initial conditions and data assimilation	Initial conditions	Initial and boundary conditions of hydrological and hydraulic models
Hydraulic model	Model unable to fully represent processes	Model unable to represent processes	Meteorological observations
	Infrastructure failure	Observed data	Model parameters
	Model parameters		
	Geometry of the system		

Being explicit in naming sources of uncertainty is challenging owing to the wide variety of flood forecasting systems. The most prevalent sources of uncertainty affecting flood forecasting systems have been identified as: uncertainty resulting from NWP forecasts, uncertainty from issues with measurements and observations, uncertainty due to initial conditions, uncertainty due to the model being unable to fully represent processes and uncertainty due to parameters. Here, NWP forecasts are classified as input data and the uncertainties are treated as a single source of uncertainty. The authors are aware that NWP originates from atmospheric prediction models and uncertainty sources can be separated out in more detail; however, this is outside the scope of this chapter[4].

In previus sections and above, described somewhat about the concept and resources of the uncertainties. In this secton to be continue more describe aboue the subjects and in other chapters will described more detail about the items.

3-3-1 NWP forecasts and Input forecast errors

Atmospheric variables that are used in flood forecasting systems include precipitation, temperature and evaporation. Precipitation is considered to be the variable that has most effect on a flood forecasting systems outputs (e.g. water level, flow) (Strauch et al., 2012)[4]. Excluding seasonal forecasts, there are three types of precipitation forecasts that are typically applied to flood forecasting systems:

I. Short to mid-range precipitation forecasts for NWP.

II. Short term rainfall forecasts and nowcasts (e.g. 0 to 9 hours) from extrapolation from weather radar rainfall estimations (Liguori and Rico-Ramirez, 2014)[4].

III. Merged NWP with radar products have been developed which combine the high spatial temporal resolution of radar nowcasting with the longer lead times of NWP forecasts.

Significant uncertainty is associated with forecasting precipitation (Bauer, et al., 2015)[4]. In radar nowcasting, uncertainty is due to a combination of uncertainty in the observations of the radar data and uncertainty in estimations in modelling the movement of the precipitation field in space and time (Liguori and Rico-Ramirez, 2014)[4]. In the NWP predictions uncertainty is due to model uncertainty, boundary and initial conditions. These uncertainties can be assessed using an ensemble (Palmer, 2000)(Chapter 4). A mismatch between the scale of the atmospheric model outputs and the required scale of the hydrological model can be solved by using downscaling techniques (Rodriquez-Rincon, et al., 2015)[4]. However, these techniques lead to uncertainties and have limitations (Fowler and Wilby, 2007)[4].

So important uncertainty introduced to flood forecasting is from the fact that meteorological forecasts are characterized by their own significant errors. It is unlikely that these can be effectively incorporated into the derivation of the conditional predictive probability of the flood forecast model. There is quite an amount of literature on this subject, but a final agreement on the best way for accounting this uncertainty has not yet been reached. Although, Meteorological practice is now progressively moving towards the provision of ensemble forecasts. The ensemble forecasts are a number of future rainfall projections from a starting point where initial conditions are subject to alternative but physically feasible developments. The output can suggest a “most likely outcome”, as well as the range of possible outcomes. The predictive probability of the ensemble method is not fixed, for example in the relationship between maximum and mean rainfall intensity, but the format of the output does allow a probability assessment of the outcome (the forecast) in each case[3].

3-3-2 Measurement and observation errors

Observations are essential to the calibration and validation of flood forecasting systems but are uncertain themselves (Gotzinger and Bardossy, 2007)[4]. Observed data are affected by both random and systematic errors varying over time. Frequently occurring uncertainties relating to the difference between the spatial and temporal characteristics of the observations compared to the model include:

I. Uncertainty due to the interpolation techniques used for applying a point measurement to areal or volumetric model inputs (Gotzinger and Bardossy, 2007)[4].

II. Uncertainty due to using a rating curve to convert water level into a discharge, for more details the reader is referred to McMillan et al., (2012) and Di Baldassarre and Montanari (2009)[4].

III. Uncertainty in remote sensing data due to the sensing and retrieval techniques used (Li et al., 2016).

IV. Uncertainty in radar rainfall observations due to the difficulties in distinguishing solid precipitation (e.g. snowflakes and hailstones), the effect of terrain blocking and inaccuracies in the reflectivity-rain rate relationship (McMillan et al., 2012).

The reader is referred to (McMillan, et al., 2012)[4] and (Li et al., 2016)[4] for a comprehensive review of uncertainty in measurements.

So input measurements from observations or estimates through fitted relationships are important source of errors. Input can include distributed or lumped rainfall, water levels or discharge estimated by a rating curve or weir equation. Errors in spatially averaged rainfall alone can easily be between 20 and 30 per cent[3], while water level measurements and discharges can be biased or affected by instrument errors[3].

To correctly estimate the “true” parameter values of a physical-process model, it is necessary to represent all the uncertain quantities in terms of their probability density curves, and the interaction or cumulative effect of all the probability functions. This is an almost impossible or atleast hard task[3,1].

3-3-3 Initial condition and boundary condition errors

The initial conditions in flood forecasting systems include the soil moisture, snow cover, initial state of the rivers and other waterbodies in the catchment (Li et al., 2009; Madsen and Skotner, 2005)[4]. Not all initial conditions can be observed or will have data available. As a solution these conditions are estimated using models, which leads to uncertainty. The continuous simulation of a flood forecast system will also inherit state uncertainty from preceding time steps (Gotzinger and Bardossy, 2007)[4]. Initial conditions that are especially associated with large uncertainty are soil moisture and snow cover (Li et al., 2009)[4].

Initial condition errors can affect not only physical-process model results, such as in the case

of flood routing or flood inundation models, but also determine extremely strong errors and forecasting uncertainty in the case of rainfall– runoff models. As an example, whatever type of model (data-driven, conceptual or physically meaningful) is used, the soil moisture content at the outset of an event may change the predicted outflow by an order of magnitude. This type of error is more severe for event-type models, for which it is extremely difficult to infer the right soil moisture. With continuous-time models, using explicit updating of the water balance in the soil, effects are less marked[3].

Errors in boundary conditions, in general also defined as time-invariant conditions, also heavily affect the forecast, particularly when dealing with physical-process models, for which the description of the terrain, the channel cross-sections and slopes and the elevation of the dykes may radically change the results. Again, boundary condition errors may be compensated by parameter estimation.

3-3-4 Model errors

The inherent simplifications of the model to represent the more complex real system leads to uncertainty. For example, distributed hydrological models use polygons or grids to represent the catchment, this will lead to uncertainty, as the physical processes (e.g. related to soil structure) often occur on smaller scales than the model elements (Gotzinger and Bardossy, 2007). An overview of different models in hydrology is provided by Todini (2007) for hydrological models and (Knight, 2013). An example of the range of uncertainty in hydrological models is presented by Haddeland et al. (2011) where 11 global models were forced with the same data. The results had significantly different results ranging from 290 to 457 mm/year depending upon the partitioning of evaporation and runoff year[4].

Models are always simple and schematic representations of reality: even the most sophisticated ones will inevitably embed schematization error. Moreover, model structures can also be wrong, for instance when a linear model is used as an approximation of a non-linear phenomenon. This implies that a small or large model error will always be inherent in any model. In general, model errors can, to a greater or lesser extent, be compensated fully or in part by parameter calibration and this can be one of the reasons why estimated parameters may strongly disagree with physically meaningful values[3,1].

3-3-5 Model parameter errors

Model parameters are related to the input data (Matott et al., 2009) but are not necessarily actual physical variables or are not directly measurable, which means they need to be calibrated to find values that are able to match the input-output behaviour of the model to the real system (Vrugt et al., 2003)[1]. The estimation or calibration processes inevitably leads to uncertainty. Parameter uncertainty will be different due to using different types of models available, e.g. conceptual, physical and black box. The parameters of a hydrological model (conceptual model) relate to catchment characteristics such as soil type, vegetation, antecedent moisture conditions. Variation in catchment characteristics leads to variation of the parameters. These local spatial heterogeneities and non-stationarities in the catchments affect the parameters, making them difficult to estimated effectively (Gupta et al., 2003). This leads to a lack of transferability of the parameters across the catchment, which will inevitably lead to uncertainty of the runoff prediction (Pappenberger et al., 2005). In the case of hydraulic models (physically based) local heterogeneities in the channel and floodplain geometry and cover will affect the parameters. Local parameters will need to be calibrated using observed data, of which are often limited. As a result there will be uncertainty with respect to the hydraulic model outputs, which can include flood inundation and the flood wave propagation (Pappenberger et al., 2005). Of course the parameters themselves can never represent reality which brings additional uncertainty due to e.g. equifinality (Beven and Freer, 2001) .

If it is assumed that the model structure represents the physical behaviour of the system as effectively as possible at its representation scale, then it would also be assumed that a successful outcome could be achieved by providing the model with physically meaningful values for the parameters. These would only need small adjustments to cope with the noninfinitesimal scale at which the ruling equations are generally derived. This is, for instance, the case of a flood routing model: the Manning's "n" can be more or less established on the basis of the known materials and the nature of the river bed and flood plain. In this case the forecasting uncertainty will be "conditional" on the model structure as well as on the parameters. However, if parameters are estimated regardless of the complexity of their statistical characteristics, they will inevitably become "sinks", to encompass all the uncertainties.

3-4 Quantifying uncertainty

To understand, analyse and compare different types of uncertainty, quantification methods are helpful to classify them into different categories. Montanari (2007) distinguishes four types of uncertainty quantification methods:

I. Approximate analytical methods; deriving uncertainty using known statistical properties of the system and input data[4,1].

II. Approximate numerical methods/sensitivity analysis; define the system space as a collection of all possible modelling solutions that can be obtained by varying the parameters and model structure. Multiple runs can then be performed randomly sampling the system and input data space, the uncertainty can be derived from the collection of outputs[4,1].

III. Techniques based on the statistical analysis of model error; statistical analysis of the model residuals of the forecast value compared to the observed values[4,1].

IV. Non-probabilistic methods; based on random set theory, evidence theory, fuzzy set theory or possibility theory which provide possibilistic information[4,1].

Methods from the first category are limited in flood forecasting due to the statistical properties of the input space being mostly unknown (Van Steenbergen et al., 2012). The fourth category is mostly relevant to situations with very limited data availability where human reasoning (possibilistic information) is used to assess the likelihood of a scenario taking place.

The most common methods in flood forecasting to quantify uncertainty fall into categories two and three. Methods do not necessarily fall into a single category, but can fall across several categories (Montanari, 2007)[4].

3-4-1 Approximate numerical methods and sensitivity analysis

The approximate numerical methods and sensitivity analysis aims to move away from the principle of a single optimum model setup, in which the model setup includes both model structure and model parameters. The philosophy behind this is that there are multiple model structures and parameters within these structure, that will provide an equally acceptable representation of the complex environment (Beven and Freer, 2001). The defined system and input space should cover all model parameters, structure and input uncertainty. Random sampling over the space is applied, allowing multiple model runs to take place (Van Steenbergen and Willems, 2015) . Observed data are not required as a direct input in this methods. The multiple model runs that are part of this methods will require additional computational power and data management resources compared to traditional deterministic methods of forecasting.

The main challenge when applying this method is defining the input and system space so that it will cover all aspects of uncertainty. Two approaches are available to this:

1) importance sampling (Kuczera and Parent, 1998); and

2) using a response surface with weights, the most common method to do this is the generalised likelihood uncertainty estimator GLUE (Beven and Freer, 2001).

An example of using resampling and multiple model runs is where the uncertainty of all model components of the flood forecasting chain were quantified (Pappenberger et al., 2005); a probabilistic weather forecast containing 50 members for instant and one control was used. The parameter uncertainty of the rainfall-runoff model was quantified using GLUE. GLUE was also applied to the flood inundation model in order to get ten different sets of roughness coefficients for example. This uncertainty analysis was applied to the European Flood Awareness System (EFAS); more details about EFAS are provided in Figure 3-5.

Box 1 Uncertainty in the European Flood Awareness system
Operating Authority: European Flood Alert system (EFAS)
Models used: LISFLOOD, a GIS based distributed hydrological rainfall runoff routing model on a 5km grid with six hourly time steps. (Van Der Knijff et al., 2010)
Forecast rainfall: Deterministic forecast rainfall from the Deutsche Wetterdienst, ECMWF deterministic and ensembles (VAREPS) and Ensembles from Consortium for Small-scale Modelling (COSMO).
Uncertainty method: The uncertainty method is based on the atmospheric uncertainty which is quantified using ensembles and weather prediction from different models. The weather predictions from the different models and the ensembles are push through the hydrological model (LISFLOOD). Warnings are probabilistic based on return period threshold exceedance.
Example output – Probabilistic threshold exceedance warnings. (ECMWF, 2016; Smith *et al.*, 2016) More information available: https://www.efas.eu/user-information.html and Thielen 2009

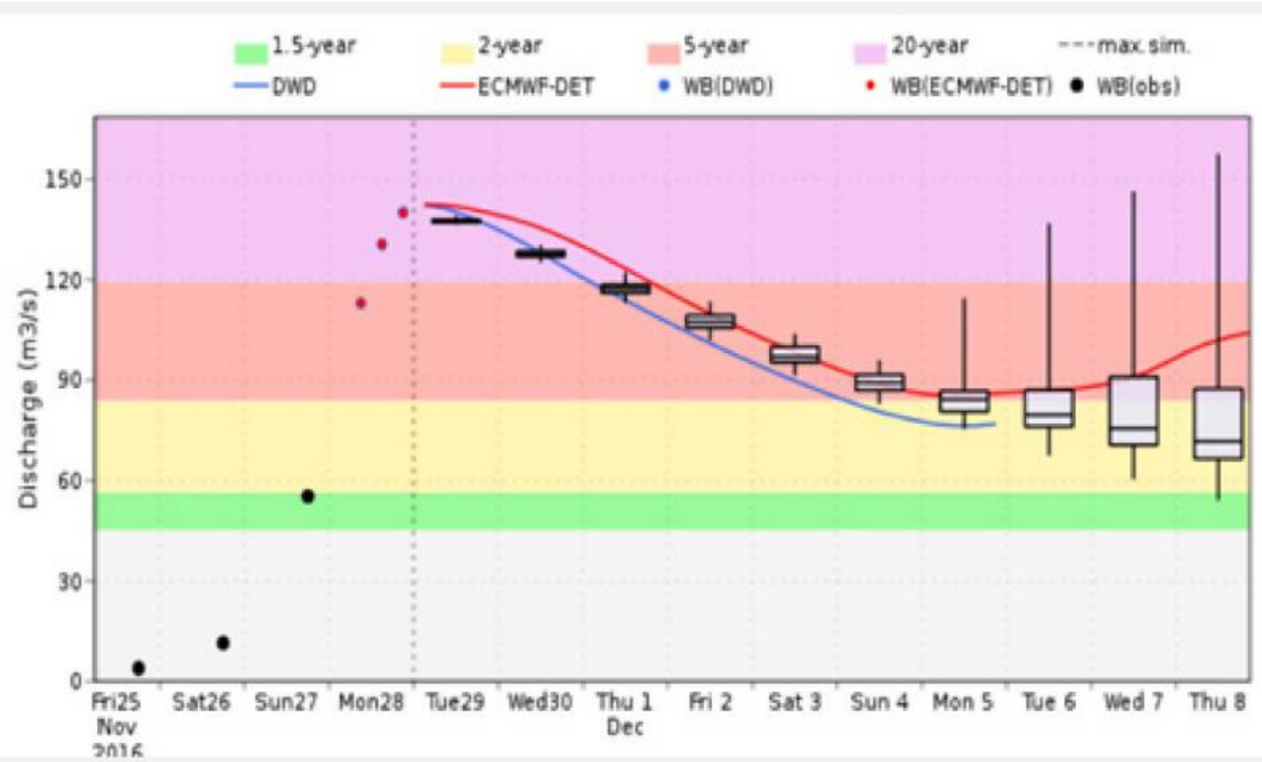

Fig. 3-5 Uncertainty in the European Flood Awareness system

3-4-2 Techniques based on the statistical analysis of model error

Techniques based on the statistical analysis of model uncertainty use statistics derived from comparing the forecast values to observed values. An example of this is the probability distribution of model residuals which can be derived by comparing, for example, forecast value of river discharge to observations (Montanari and Brath, 2004). This method assumes that the future uncertainty can be represented using the model residuals of past forecasts. This method is attractive due to the low requirements with regards to computational power and data management, because multiple model runs are not required. When dealing with data scarce locations the application of this method is limited, due to observed data being directly used. From the perspective of observed data being in itself uncertain, this method has a limited ability quantify uncertainty correctly (Montanari and Brath, 2004). Assumptions regarding stationarity and ergodicity of the model residuals are often required, but remain disputed for different systems and for different states of a system.

An example of the application of this method is given by Weerts et al. (2011) when they aim to quantify the predictive uncertainty of the rainfall-runoff and hydraulic forecasts. A retrospective quantile regression is applied to the hindcast water level. Independent sources of uncertainty are not considered, instead the effective uncertainty of the forecast process is considered, which can be a result of input or output uncertainty, model structural uncertainty or parameter uncertainty. The method has been tested for robustness on catchments across England and Wales of different sizes and hydrological characteristics (Weerts et al., 2011).

3-4-3 Combined methods

Other methods, such as approximate analytical methods; and non-probabilistic methods; based on random set theory, evidence theory, fuzzy set theory or possibility theory which provide possibilistic information can be used.

The two methods model error and Approximate numerical methods and sensitivity analysis represent two different approaches to quantifying uncertainty in flood forecast systems. However, due to the fact that flood forecasting systems consist of multiple components, there are forecasting systems that use a combination of these two methods. An example is described by Krzysztofwicz and Herr (2001), where a Bayesian formulation of a Hydrological Uncertainty Processor (HUP) was used in combination with probabilistic precipitation forecast. The HUP aims to quantify the aggregate of all uncertainties arising from sources other than those quantified by the probabilistic precipitation forecast. This system has been applied to the National Weather Service for a 1,430 km2 catchment in Pennsylvania, USA. The probabilistic precipitation forecast was generated using the numerical method, but the HUP is part of the model error method.

3-5 Warnings and dissemination Uncertainties [2]

It is also important to compute uncertainties in the forecasts and incorporate these as an integral part of warnings. The flood warning and dissemination process is a complex and critical component of the FFWS system that involves two distinct stages:

(1) creation and transmission of forecasts and warnings to end users, and

(2) response.

A prompt and wide coverage of flood warning is the key to a successful FFWS, but an accurate forecast without adequate planning and communication will fail to achieve the intended responses by the exposed community, including the evacuation of vulnerable groups (e.g. very young or old and mobility-limited) who are unable to respond quickly to warnings, movement of assets (food, livestock, moveable goods, etc.; Wood et al. 2015) to safer locations, efficient and timely operation of flood regulation infrastructure, and initiation of flood fighting measures. Key factors in dissemination include packaging information into forms that are understandable and usable by end users, and the rapidity with which information is communicated to them[2].

Information must be targeted to the range of end users of the FFs, which include disaster managers, municipalities and local government officers, affected population, and infrastructure managers. Forecasts are also sent to decision makers to help visualize how an event is likely to develop, how significant it will be upon arrival, and what sections of the population will likely be at risk. Emergency services and media agencies need clear information that defines the hazard. Establishing a user group association or an inventory of users is important for a well-functioning and effective FFWS.

Dissemination of forecasts and warnings may be achieved through a variety of communication methods, such as internet, flood bulletins to disaster management authorities (including police and fire departments), television, radio, telephone, bulk SMS, sirens, flags, and social media (i.e. Facebook,Twitter). In remote locations, local radio, if present, may be the most reliable means for disseminating information in local language. Other locally available alert systems, such as community/ temple bells and loud speakers, can be an effective means and have shown success in Nepal and Bangladesh.

Administrative barriers to data availability, across geopolitical boundaries and within the same boundary but across different agencies, also hamper FF. The consequences are that lead time is compromised and unreliable forecasts may be issued.

The design of a FFWS is technical but its implementation is non-technical. The non-technical aspects are primarily logistics and administrative and include preparation, accumulation of needed amenities, plans for evacuation, facilities for transportation of people, issuance of warning, communication systems, electrical systems, shelter for people, food and clothing, medical supplies, manpower for help, counselling, among others. The effectiveness of an FFWS greatly depends on these nontechnical aspects. It is important that technical and non-technical aspects are seamlessly integrated. Often, a simple FFWS may work well, provided non-technical issues are properly addressed.

Communication systems, especially in developing countries, are often vulnerable in times of severe flooding and are rendered inoperative when they are needed most. In these areas, back-up communication systems and educational campaigns are needed to help the general public understand the various facets of floods so that they follow warnings and protect themselves even in the absence of any warning. During and after flooding, adequate relief measures must be provided at short notice, which requires that administrators have the technical, financial, and political resources to prepare in advance and respond quickly and effectively. Likewise, post-flood disaster, people should be helped so that they can become more resilient to future potential floods.

3-5-1 Predictive uncertainty in operation [3]

When dealing with flood emergency management, operational decisions may lead to dramatic consequences (economical losses and casualties). Nonetheless, emergency managers are required to take decisions under the stress of their uncertainty about the evolution of future events. Decision theory has developed into an extensive topic of mathematical study. One of the issues in the debate among hydrologists is how to demonstrate the benefits arising from the operational use of predictive uncertainty. The corollary of this is how to communicate uncertainty to the end-users, namely the decision makers such as water and emergency managers, who may have a certain difficulty in perceiving these benefits.

Statements such as “the probability of flooding within the next 12 hours is 67.5 per cent” is often meaningless to an end-user. The information has to answer the basic question “what are the expected benefits and drawbacks of issuing a flood alert for the next 12 hours?”. Therefore, hydrologists must define, in dialogue with end-users, subjective utility functions, which can be used to compute the expected benefits or damages contingent on the predictive density of the quantity of interest. A schematic example of such utility functions is shown in Figure 3-6, for the case of a flood alert (note that in this simple schematic example, casualties are not taken into account).

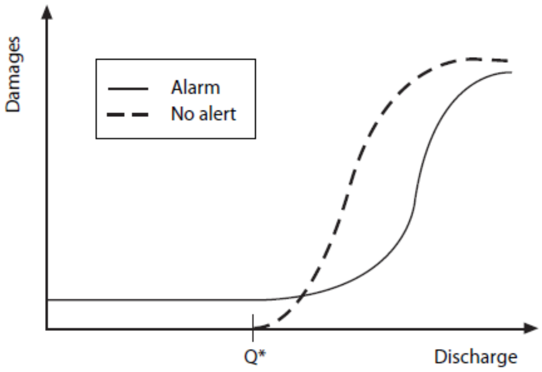

Figure 3-6. The utility functions deriving from a flood alert problem: solid line represents cost and damage perceived by the end-user if an alert is issued; dashed line represents perceived cost and damage if an alert is not issued; Q* is the maximum discharge that may safely flow in the river[3]

The dashed line represents the end-user perception of the damage (not necessarily the real one) that will occur if the dykes are overtopped, namely if Q > Q*, where Q* is the maximum discharge that may safely flow in the river. The solid line represents the perception of cost plus damages when an alert has been issued. As can be seen from Figure 3-6, if an alert is issued a cost must inevitably be incurred for mobilizing civil protection agents, alerting the population, laying sandbags and taking other necessary measures. However, the damage in that case will be smaller than in the “no-alert” case, due to the raised awareness of the incoming flood.

The decision on whether or not to issue an alert will then depend on the comparison of the "expected damage" for the two options, obtained by integrating the product of the **cost function** multiplied by the predictive uncertainty probability density function over all possible values of future discharge. It should be noted that the "expected damages" are a function of the actual future discharge that will happen, not of the discharge predicted by the model. By using the expected value of damage instead of the "model forecast", the probability of false alarms as well as of missed alarms should be much reduced, as the uncertainty about the future discharge is taken into account. In addition, the peakier the predictive density is, the more reliable will the resulting decision be, so that improvements in forecasting, rather than looking for a better "deterministic" forecast, must essentially aim at reducing predictive uncertainty by whatever means is available.

To show how predictive uncertainty can be used in operation, the Lake Como real-time management decision support system is given as one of the few existing successful examples (Todini and Bongioannini Cerlini, 1999)[3]. Lake Como is a natural lake in northern Italy closed at its exit and managed as a multi-purpose lake for flood control, irrigation and electric power production. Using a stochastic dynamic programming approach, a standard operating rule was developed on a 10 day basis to optimize long-term irrigation and energy production. However, when a flood is forecast, the reservoir manager needs to modify the standard operating rule. To achieve this, a utility function describing the damage perception of the manager was developed. Every morning an incoming flood forecast, together with its predictive uncertainty, is issued, and an optimal release, computed by minimizing the expected damage using the inflow predictive uncertainty, is then proposed. All this process is totally hidden from the water manager, who is aware only of the suggested optimal release and of its expected consequences (Fig 3-7). The performance of the system was assessed on the basis of a hindcast simulation for the 15-year period from 1 January 1981 to 31 December 1995. The results are presented in the table 3-2. When applying the optimized rule, the lake level never fell below the acceptable lower limit of –0.4 metres, while historically this was observed on 214 days. In terms of Como flooding, over the 15 years the lake level has been recorded to be above the lower flood limit of 1.2 metres on 133 days, whereas the optimized rule reduced it to 75 days. A noticeable reduction also appears at higher lake levels. At 1.4 metres, when the traffic must stop in the main square of Como, the reduction is from 71 to 52 days and at 1.73 metres, the legal definition of "normal flood" when people can claim compensation for their damage, the reduction is from 35 to 34 days.

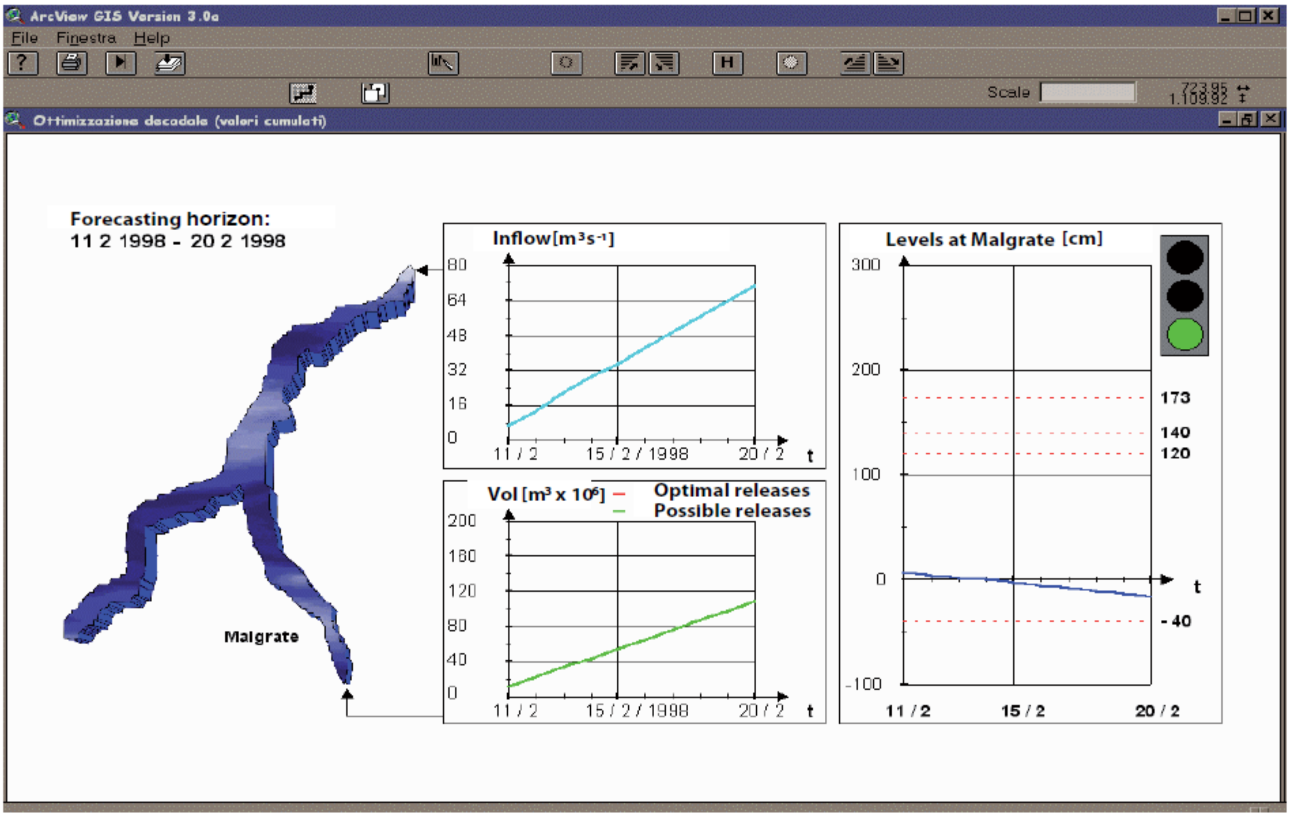

Figure 3-7 The Lake Como operational decision support system.

The system, on the basis of the expected

value of inflows to the lake (light blue line) and its uncertainty (not shown, but used in the process)

suggests to the water manager the optimal (red line – not shown) and possible (green line) releases that

minimize the expected damage. It also shows the consequent expected lake level (blue line)

for the following 10 days[3].

Table 3-2 Summary of the results of a comparison between recorded water level occurrences and water deficits (historical) and the results of the operation rule based on the forecasting uncertainty (optimized) for the 15-year period from 1 January 1981 to 31 December 1995[3]

Water level	*Number of days*	
	Historical	*Optimized*
–40 cm	214	0
120 cm	133	75
140 cm	71	52
173 cm	35	34
Water deficit:	890.27×10^6 m^3	788.59×10^4 m^3

At the same time, the irrigation water deficit decreased by an average of more than 100 × 106 cubic metres per year. This result is exceptional, given that meeting irrigation demand implies higher lake levels, an objective conflicting with the need to reduce the frequency of flooding.

It is quite interesting how the system was accepted by the end-user. At the end of 1997, the system was installed operationally and the Director of Consorzio dell'Adda, who is in charge of lake management, was invited to look at it but not to use it until he had confidence in its effectiveness. After six months the Director admitted that he had made a wrong decision on all of four occasions when the decision support system (DSS) had provided a solution. Ever since, the system has been in operation and used successfully. It has produced not only a reduction in the number, frequency and magnitude of Como flooding events, but also a 3 per cent increase in energy production and a large volume of extra water for irrigation.

The above example shows that, if appropriately briefed and involved, the end-users will quickly become aware of the benefits arising from the use of predictive uncertainty, provided they are not asked to interpret the forecasting in statistical terms or the stochastic computation and optimization frequently required in problems in this type.

Considerable effort is still required to inform the end-users of the improvements obtainable without burdening them with the computational complexity.In this way, they will appreciate and receive the full benefits of an approach aimed at improving the success of their decision-making.

3-6 Conclusions

Two main challenges have been identified as part of this review on the understanding and quantification of uncertainty for flood forecasting systems. The first challenge is that there is a lack of coherent terminology around uncertainty in flood forecasting. Calls for a more coherent terminology, for example by Montanari (2007)[4], have thus far proven difficult to achieve. It could be that the difficulty lies in finding terminology around uncertainty that will be applicable to the wide variety of systems within flood forecasting. Another difficulty lies in the fact that flood forecasting brings together a wide variety of different disciplines, including meteorologists, hydrologists, IT, electronic, mathematicians, civil and social scientists.

The second challenge that has been identified is that the remaining mathematical and theoretical challenges in the quantification of uncertainty requires assumptions to be made that could be leading to a misrepresentation of the predictive uncertainty. More specifically for approximate numerical methods and sensitivity analysis creating a usable ensemble that covers the input and system space remains a challenge. In the case of techniques based on the statistical analysis of model uncertainty the questions around how representative the historical model residuals are for the future uncertainty remain unanswered.

Opportunities to improve uncertainty quantification methods can be found for example in the field of data assimilation and in many cases the coming together of research form different disciplines can be instrumental in developing better methods[4].

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Chapter 4 Weather Forecasting

"**James Glaisher** was an English meteorologist, aeronaut and astronomer.In 1845, Glaisher published his dew point tables for the measurement of humidity. Glaisher made numerous ascents to measure the temperature and humidity of the atmosphere at its highest levels. Estimates suggest that he rose to more than 9,500 metres above sea level"

4-1 History

After first Glasher works, the history of numerical weather prediction (NWP) began in the 1920s through the efforts of Lewis Fry Richardson, who used procedures originally developed by Vilhelm Bjerknes to produce by hand a six-hour forecast for the state of the atmosphere over two points in central Europe, taking at least six weeks to do so (Fig. 4-1).

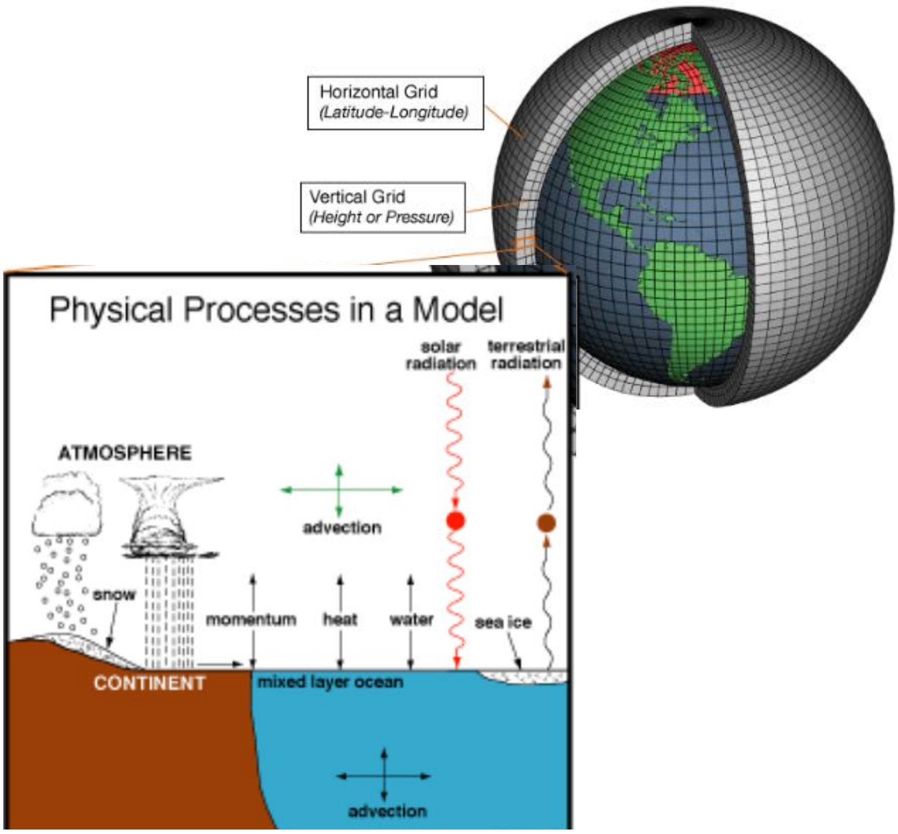


Fig.4-1 Weather models use systems of differential equations based on the laws of physics, which are in detail fluid motion, thermodynamics, radiative transfer, and chemistry, and use a coordinate system which divides the planet into a 3D grid. Winds, heat transfer, solar radiation, relative humidity, phase changes of

water and surface hydrology are calculated within each grid cell, and the interactions with neighboring cells are used to calculate atmospheric properties in the future.

It was not until the advent of the computer and computer simulations that computation time was reduced to less than the forecast period itself.

The ENIAC (**Electronic Numerical Integrator and Computer,** University of Pennsylvania, its first program was a study of the feasibility of the thermonuclear weapon) was used to create the first weather forecasts via computer in 1950, based on a highly simplified approximation to the atmospheric governing equations. In 1954, Carl-Gustav Rossby's group at the Swedish Meteorological and Hydrological Institute used the same model to produce the first operational forecast (i.e., a routine prediction for practical use).

Operational numerical weather prediction in the United States began in 1955 under the Joint Numerical Weather Prediction Unit (JNWPU), a joint project by the U.S. Air Force, Navy and Weather Bureau.] In 1956, Norman Phillips developed a mathematical model which could realistically depict monthly and seasonal patterns in the troposphere; this became the first successful climate model. Following Phillips' work, several groups began working to create general circulation models, (GCM, entire earth). The first general circulation climate model that combined both oceanic and atmospheric processes was developed in the late 1960s at the NOAA Geophysical Fluid Dynamics Laboratory.

As computers have become more powerful, the size of the initial data sets has increased and newer atmospheric models have been developed to take advantage of the added available computing power. These newer models include more physical processes in the simplifications of the equations of motion in numerical simulations of the atmosphere. In 1966, West Germany and the United States began producing operational forecasts based on primitive-equation models, followed by the United Kingdom in 1972 and Australia in 1977.

The development of limited area (regional) models facilitated advances in forecasting the tracks of tropical cyclones as well as air quality in the 1970s and 1980s. By the early 1980s models began to include the interactions of soil and vegetation with the atmosphere, which led to more realistic forecasts.

The output of forecast models based on atmospheric dynamics is unable to resolve some details of the weather near the Earth's surface. As such, a statistical relationship between the output of a numerical weather model and the ensuing conditions at the ground was developed in the 1970s and

1980s, known as model output statistics (MOS). Starting in the 1990s, model ensemble forecasts have been used to help define the forecast uncertainty and to extend the window in which numerical weather forecasting is viable farther into the future than otherwise possible.

4-2 Applications

Some other applications of NWP except of flood forecasting, wind erosion, agriculture management and .. etc are:

Wildfire modeling

On a molecular scale, there are two main competing reaction processes involved in the degradation of cellulose, or wood fuels, in wildfires. When there is a low amount of moisture in a cellulose fiber, volatilization of the fuel occurs; this process will generate intermediate gaseous products that will ultimately be the source of combustion. When moisture is present—or when enough heat is being carried away from the fiber, charring occurs. The chemical kinetics of both reactions indicate that there is a point at which the level of moisture is low enough—and/or heating rates high enough—for combustion processes become self-sufficient. Consequently, changes in wind speed, direction, moisture, temperature, or lapse rate at different levels of the atmosphere can have a significant impact on the behavior and growth of a wildfire. Since the wildfire acts as a heat source to the atmospheric flow, the wildfire can modify local advection patterns, introducing a feedback loop between the fire and the atmosphere. A simplified two-dimensional model for the spread of wildfires that used convection to represent the effects of wind and terrain, as well as radiative heat transfer as the dominant method of heat transport led to reaction-diffusion systems of partial differential equations (Fig. 4-2).

More complex models join numerical weather models or computational fluid dynamics models with a wildfire component which allow the feedback effects between the fire and the atmosphere to be estimated. The additional complexity in the latter class of models translates to a corresponding increase in their computer power requirements. In fact, a full three-dimensional treatment of combustion via direct numerical simulation at scales relevant for atmospheric modeling is not currently practical because of the excessive computational cost such a simulation would require. Numerical weather models have limited forecast skill at spatial resolutions under 1 kilometer (0.6 mi), forcing complex wildfire models to parameterize the fire in order to calculate how the winds will be modified locally by the wildfire, and to use those modified winds to determine the rate at which the fire will spread locally. Although **models** such as **Los Alamos' FIRETEC** solve for the concentrations of fuel and oxygen, the computational grid cannot be fine enough to resolve the combustion reaction, so approximations must be made for the temperature distribution within each grid cell, as well as for the combustion reaction rates themselves.

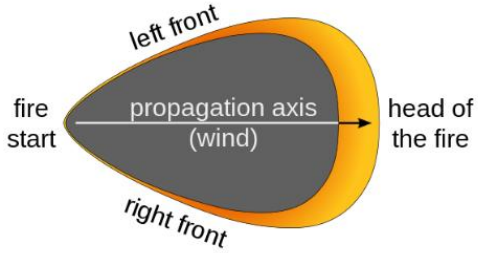


Fig. 4-2: A simple wildfire propagation model

Climate modeling (Global Climate Model)

A General Circulation Model (**GCM**) is a mathematical model that can be used in computer simulations of the global circulation of a planetary atmosphere or ocean. An atmospheric general circulation model (AGCM) is essentially the same as a global numerical weather prediction model, and some (such as the one used in the UK Unified Model) can be configured for both short-term weather forecasts and longer-term climate predictions. Along with sea ice and land-surface components, AGCMs and oceanic GCMs (OGCM) are key components of global climate models, and are widely applied for understanding the climate and projecting climate change. For aspects of climate change, a range of man-made **chemical emission scenarios** can be fed into the climate models to see how an enhanced greenhouse effect would modify the Earth's climate.

Versions designed for climate applications with time scales of decades to centuries were originally created in 1969 by Syukuro Manabe and KirkBryan at the **Geophysical Fluid Dynamics Laboratory in Princeton, New Jersey**. When run for multiple decades, computational limitations mean that the models must use a coarse grid that leaves smaller-scale interactions unresolved (Fig 4-1).

Ocean surface modeling (Marine weather forecasting, Ocean dynamics, and Wind wave model)

The transfer of energy between the wind blowing over the surface of an ocean and the ocean's upper layer is an important element in wave dynamics. The **spectral wave transport** equation is used to describe the change in wave spectrum over changing topography. It simulates wave generation, wave movement (propagation within a fluid), wave shoaling, refraction, energy transfer between waves, and wave dissipation. Since surface winds are the primary forcing mechanism in the spectral wave transport equation, ocean wave models use information produced by **numerical weather prediction models** as inputs to determine how much energy is transferred from the atmosphere into the layer at the surface of the ocean.

Along with dissipation of energy through whitecaps and resonance between waves, surface winds from numerical weather models allow for more accurate predictions of the state of the sea surface (Fig. 4-3).

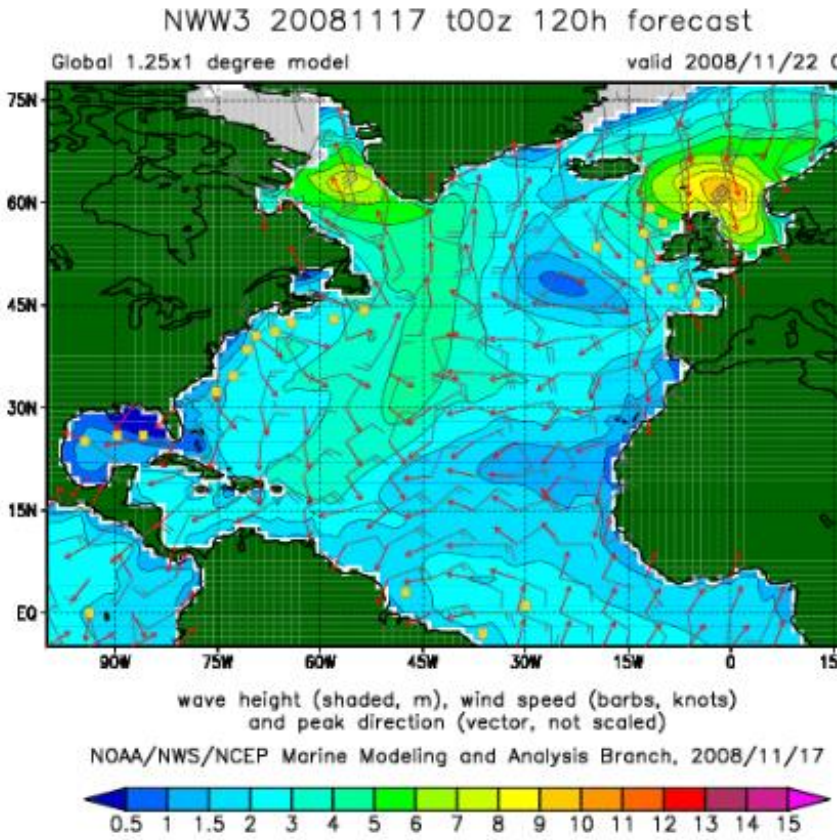


Fig. 4-3 NOAA Wavewatch III 120-hour wind and wave forecast for the North Atlantic

Tropical cyclone forecasting

Tropical cyclone forecasting also relies on data provided by **numerical weather models**. Three main classes of tropical cyclone guidance models exist:

1-Statistical models are based on an analysis of storm behavior using climatology, and correlate a storm's position and date to produce a forecast that is not based on the physics of the atmosphere at the time.

2- Dynamical models are numerical models that solve the governing equations of fluid flow in the atmosphere; they are based on the same principles as other **limited-area numerical weather prediction models** but may include special computational techniques such as refined spatial domains that move along with the cyclone.

3-Models that use elements of both approaches are called statistical-dynamical models.

In 1978, the first hurricane-tracking model based on atmospheric dynamics—the movable fine-mesh (MFM) model—began operating. Within the field of tropical cyclone track forecasting, despite the ever-improving dynamical model guidance which occurred with increased computational power, it was not until the 1980s when numerical weather prediction showed skill, and until the 1990s when it consistently outperformed statistical or simple dynamical models. Predictions of the intensity of a tropical cyclone based on numerical weather prediction continue to be a challenge, since statistical methods continue to show higher skill over dynamical guidance.

Air quality modeling (Atmospheric dispersion modeling)

Air quality forecasting attempts to predict when the concentrations of pollutants will attain levels that are hazardous to public health. The concentration of pollutants in the atmosphere is determined by their *transport*, or mean velocity of movement through the atmosphere, their diffusion, chemical transformation, and ground deposition. In addition to pollutant source and terrain information, these models require data about the state of the fluid flow in the atmosphere to determine its transport and diffusion. Meteorological conditions such as thermal inversions can prevent surface air from rising, trapping pollutants near the surface, which makes accurate forecasts of such events crucial for air quality modeling. Urban air quality models require a very fine computational mesh, requiring the use of high-resolution **mesoscale weather models**; in spite of this, the quality of numerical weather guidance is the main uncertainty in air quality forecasts.

4-3 Numerical weather prediction

Weather Forecasters, who to interpret results of the various numerical weather prediction (NWP) models. Numerical weather prediction models, or NWP, solve a complex set of **mathematical equations** that are based on the **physics** that drives how the air moves and how heat and moisture are exchanged throughout the atmosphere.

Numerical Weather Prediction (NWP) uses the power of computers to make a **forecast**. A forecaster examines how the features **predicted** by the computer will interact to produce the day's **weather**. The NWP method is flawed in that the equations used by the models to simulate the atmosphere are not precise. So uncertainty analysis in input data is a vital step.

Weather models use systems of differential equations based on the laws of physics, which are in detail fluid motion, thermodynamics, radiative transfer, and chemistry, and use a coordinate system which divides the planet into a 3D grid(Fig4-4), Winds, heat transfer, solar radiation, relative humidity, phase changes of water and surface hydrology (snow, ice, evaporation,…) are calculated within each grid cell, and the interactions with neighboring cells are used to calculate atmospheric properties in the future.

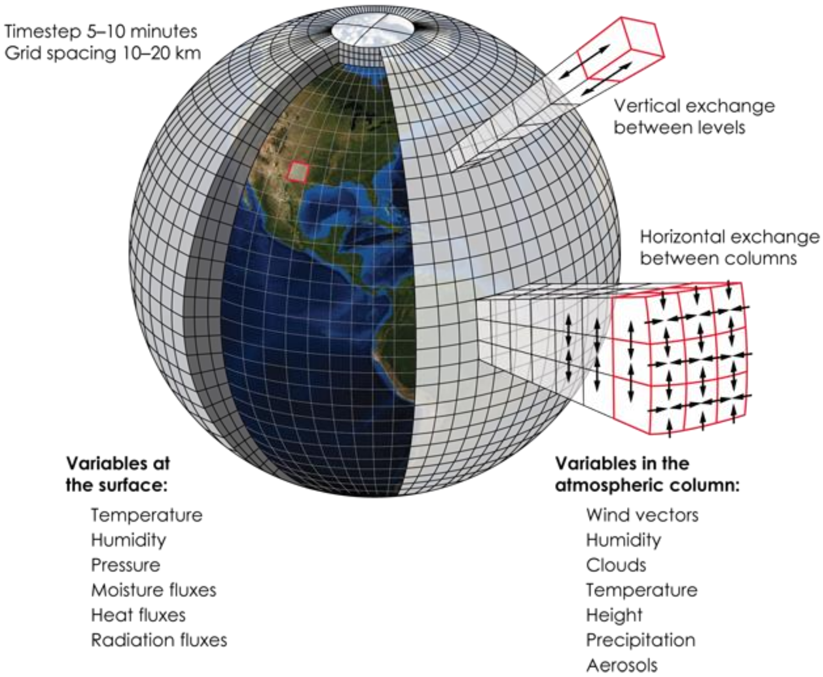


Fig 4-4 Weather forecast modeling

The two best-known NWP models are the National Weather Service's Global Forecast System, or **GFS**, and the European Center for Medium-Range Weather Forecast, known as the **ECMWF** model. They are also known as the **American and European models**, respectively. Generally speaking, the European model has produced the most accurate global weather forecasts.

If **physics** drives these models, how can these NWP models result in different weather predictions? Because of the complexity of the mathematical equations, each model has to make some approximations, and these approximations may differ. In addition, each model assimilates observations a bit differently.

A numerical forecast is only as accurate as the observations that go into the forecast at the beginning of its run, also known as the "initial conditions." Because weather moves from one place to another rapidly, tomorrow's weather is influenced by today's weather far upstream, and next week's weather can be affected by today's weather a continent away. For this reason, forecasters need lots of worldwide data. Today we have global sources of data of many different types to give the forecast the best possible start.

Mathematical models based on the same physical principles can be used to generate either short-term weather forecasts or longer-term climate predictions; the latter are widely applied for understanding and projecting climate change. The improvements made to regional models have allowed for significant improvements in tropical cyclone track and air quality forecasts; however, atmospheric models perform poorly at handling processes that occur in a relatively constricted area, such as wildfires.

Manipulating the vast datasets and performing the complex calculations necessary to modern numerical weather prediction requires some of the most powerful supercomputers in the world. Even with the increasing power of supercomputers, the forecast skill of numerical weather models extends to only about six days.

Factors affecting the accuracy of numerical predictions include the density and quality of observations used as input to the forecasts, along with deficiencies in the numerical models themselves. Post-processing techniques such as model output statistics (MOS) have been developed to improve the handling of errors in numerical predictions. A more fundamental problem lies in the chaotic nature of the partial differential equations (PDE) that govern the atmosphere. A partial differential equation (PDE) for the function u(x1,… xn) is an equation of the form:

$$f\left(x_1,\dots x_n;u,\frac{\partial u}{\partial x_1},\dots\frac{\partial u}{\partial x_n};\frac{\partial^2 u}{\partial x_1\partial x_1},\dots\frac{\partial^2 u}{\partial x_1\partial x_n};\dots\right)=0.$$

It is impossible to solve these equations exactly, and small errors grow with time (doubling about every five days). Present understanding is that this chaotic behavior limits accurate forecasts to about 14 days even with accurate input data and a flawless model. In addition, the partial differential equations used in the model need to be supplemented with parameterizations for solar radiation, moist processes (clouds and precipitation), heat exchange, soil, vegetation, surface water, and the effects of terrain. In an effort to quantify the large amount of inherent uncertainty remaining in numerical predictions, ensemble forecasts have been used since the 1990s to help gauge the confidence in the forecast, and to obtain useful results farther into the future than otherwise possible. This approach analyzes multiple forecasts created with an individual forecast model or multiple models.

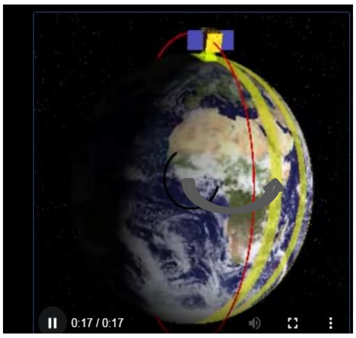
4-3-1 Weather observations

The World Meteorological Organization acts to standardize the instrumentation, observing practices and timing of these observations worldwide. Stations either report hourly in METAR reports, or every six hours in SYNOP reports. A number of global and regional forecast models are run in different countries worldwide, using current weather observations relayed from radiosondes, weather satellites, Radar and other observing systems as inputs. These observations are irregularly spaced, so they are processed by data assimilation and objective analysis methods, which perform quality control and obtain values at locations usable by the model's mathematical algorithms. The data are then used in the model as the starting point for a forecast.

4-3-1-1 Weather satellites

Information from weather satellites (Fig. 4-5) is used where traditional data sources are not available or this data is vital. Satellites can be polar orbiting, covering the entire Earth asynchronously, or geostationary, hovering over the same spot on the equator (Fig. 4-6).

Fig. 4-5 GOES-8, A United States weather satellite



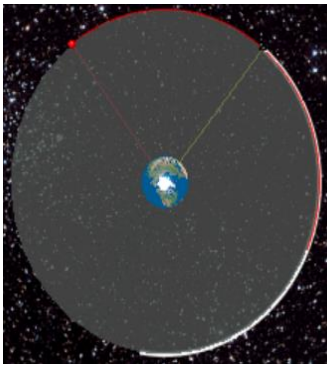


Fig. 4-6 weather satellite: Polar orbit weather satellite (Left), Two geostationary satellites in the same orbit (Right)

Geostationary weather satellites orbit the Earth above the equator at altitudes of 35,880 km (22,300 miles). Because of this orbit, they remain stationary with respect to the rotating Earth and thus can record or transmit images of the entire hemisphere below continuously with their visible-light and infrared sensors. The news media use the geostationary photos in their daily weather presentation as single images or made into movie loops. Several geostationary meteorological spacecraft are in operation. The United States' GOES series has three in operation: GOES-15, GOES-16 and GOES-17. GOES-16 and-17 remain stationary over the Atlantic and Pacific Oceans, respectively. GOES-15 has retired in July 2019.
Polar orbiting weather satellites circle the Earth at a typical altitude of 850 km (530 miles) in a north to south (or vice versa) path, passing over the poles in their continuous flight. Polar orbiting weather satellites are in sun-synchronous orbits, which means they are able to observe any place on Earth and will view every location twice each day with the same general lighting conditions due to the near-constant local solar time. Polar orbiting weather satellites offer a much better resolution than their geostationary counterparts due their closeness to the Earth. The United States has the NOAA series of polar orbiting meteorological satellites, presently NOAA-15, NOAA-18 and NOAA-19 (POES) and NOAA-20 (JPSS).
Meteorological satellites see more than clouds: city lights, fires, effects of pollution, auroras, sand and dust storms, snow cover, ice mapping, boundaries of ocean currents, energy flows, volcanic ash cloudetc, and also El Niño and its effects on weather are monitored daily from satellite images. The Antarctic ozone hole is mapped from weather satellite data too. Observation is typically made via different 'channels' of the electromagnetic spectrum, in particular, the visible and infrared portions.
The United States Department of Defense's Meteorological Satellite (DMSP) can "see" the best of all weather vehicles with its ability to detect objects almost as 'small' as a huge oil tanker. In addition, of all the weather satellites in orbit, only DMSP can "see" at night in the visual. Some of the most spectacular photos have been recorded by the night visual sensor; city lights, volcanoes, fires, lightning, meteors, oil field burn-offs, as well as the Aurora Borealis and Aurora Australis have been captured by this 450-mile-high space vehicle's low moonlight sensor.

4-3-1-2 Radiosondes

*A **radiosonde** is an automatic radio transmitter in the meteorological aids service usually carried on an aircraft, free balloon, kite or parachute, and which transmits meteorological data. Each radio transmitter shall be classified by the radio communication service in which it operates permanently or temporarily.*
So ,a radiosonde is a battery-powered telemetry instrument carried into the atmosphere usually by a weather balloon that measures various atmospheric parameters and transmits them by radio to a ground receiver. Modern radiosondes measure or calculate the following variables:

altitude, pressure, temperature, relativehumidity, wind (both windspeed and winddirection), cosmic ray readings at high altitude and geographical position (latitude/longitude). Radiosondes measuring ozone concentration are known as ozonesondes.The main inputs from country-based weather services are observations from this devices often based on weather balloons that measure various atmospheric parameters and transmits them to a fixed receiver, as well as from weather satellites. Sites launch radiosondes in weather balloons which rise through the troposphere and well into the stratosphere.

Radiosondes may operate at a radio frequency of 403 MHz or 1680 MHz. A radiosonde whose position is tracked as it ascends to give wind speed and direction information is called a **rawinsonde** ("radar wind -sonde"). Most radiosondes have radar reflectors and are technically rawinsondes. A radiosonde that is dropped from an airplane and falls, rather than being carried by a balloon is called a dropsonde.

Worldwide there are about 1,300 radiosonde launch sites. Most countries share data with the rest of the world through international agreements. Nearly all routine radiosonde launches occur 45 minutes before the official observation time of 0000 UTC and 1200 UTC, so as to provide an instantaneous snapshot of the atmosphere. This is especially important for numerical modeling. In the United States the National Weather Service is tasked with providing timely upper-air observations for use in weather forecasting, severe weather watches and warnings, and atmospheric research. The National Weather Service launches radiosondes from 92 stations in North America and the Pacific Islands twice daily. It also supports the operation of 10 radiosonde sites in the Caribbean.

Raw upper air data is routinely processed by supercomputers running numerical models. Forecasters often view the data in a graphical format, plotted on thermodynamic diagrams such as Skew-T log-P diagrams, Tephigrams, and or Stüve diagrams, all useful for the interpretation of the atmosphere's vertical thermodynamics profile of temperature and moisture as well as kinematics of vertical wind profile.

Radiosonde data is a crucially important component of numerical weather prediction. Because a sonde may drift several hundred kilometers during the 90- to 120-minute flight, there may be concern that this could introduce problems into the model initialization. However, this appears not to be so except perhaps locally in jet stream regions in the stratosphere.

4-3-1-3 Weather radar

Weather radar, also called **weather surveillance radar** (**WSR**) and **Doppler weather radar**, is a type of radar used to locate precipitation, calculate its motion, and estimate its type (rain, snow, hail etc.). Modern weather radars are mostly pulse-Doppler radars, capable of detecting the motion of rain droplets in addition to the intensity of the precipitation. Both types of data can be analyzed to determine the structure of storms and their potential to cause severe weather (Fig 4-7).

After war II, surplus radars were used to detect precipitation. Since then, weather radar has evolved on its own and is now used by national weather services, research departments in universities (3), and in television stations' weather departments. Raw images are routinely used and specialized software can take radar data to make short term forecasts (Nowcasting) of future positions and intensities of rain, snow, hail, and other weather phenomena. Radar output is even incorporated into numerical weather prediction models to improve analyses and forecasts.

Another important use of radar data is the ability to assess the amount of precipitation that has fallen over large basins, to be used in hydrological calculations; such data is useful in flood control, sewer management and dam construction. The computed data from radar weather may be used in conjunction with data from ground stations.

To know the vertical structure of clouds, in particular thunderstorms or the level of the melting layer, a vertical cross-section product of the radar data is available. This is done by displaying only the data along a line, from coordinates A to B, taken from the different angles scanned.

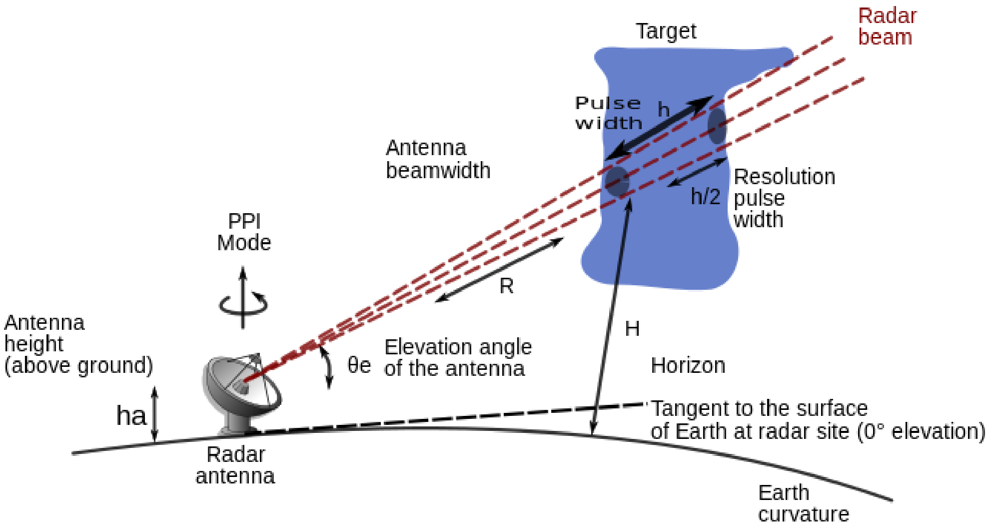


Fig. 4-7 The radar beam path with height

4-3-1-4 Other observing systems and equipments

Commerce provides pilot reports along aircraft routes and ship reports along shipping routes. Research projects use reconnaissance aircraft to fly in and around weather systems of interest, such as tropical cyclones. Reconnaissance aircraft are also flown over the open oceans during the cold season into systems which cause significant uncertainty in forecast guidance, or are expected to be of high impact from three to seven days into the future over the downstream continent. Main weather equpments are:

- Anemometer
- Atmometer
- Barograph, Barometer
- Ceiling balloon, Ceiling projector, Ceilometer
- Dark adaptor goggles
- Dewcell
- Disdrometer
- Dropsonde
- Field mill
- Heat flux sensor
- Hygrometer
- Ice accretion indicator
- Lidar
- Lightning detector
- Nephelometer, Nephoscope
- Pan evaporation
- Pyranometer
- Pyrheliometer
- Radiosonde
- Rain gauge
- Snow gauge, Snowboard, Snow pillow
- SODAR
- Solarimeter
- Sounding rocket
- Stevenson screen
- Sunshine recorder
- Tethersonde
- Thermo-hygrograph, Thermometer
- Tide gauge
- Transmissometer
- Weather balloon, buoy, vane
- Whole sky camera
- Wind profiler
- Windsock
- Automatic weather station (AWS)
- Hurricane Hunters
- Mesonet

4-3-1-5 Data assimilation

Models are *initialized* using this observed data. The irregularly spaced observations are processed by data assimilation and objective analysis methods, which perform quality control and obtain values at locations usable by the model's mathematical algorithms (usually an evenly spaced grid). The data are then used in the model as the starting point for a forecast.

Data assimilation is a mathematical discipline that seeks to optimally combine theory (usually in the form of a numerical model) with observations. There may be a number of different goals sought, for example—to determine the optimal state estimate of a system, to determine initial conditions for a numerical forecast model, to interpolate sparse observation data using (e.g. physical) knowledge of the system being observed, to train numerical model parameters based on observed data. Depending on the goal, different solution methods may be used. Data assimilation is distinguished from other forms of machine learning, image analysis, and statistical methods in that it utilizes a dynamical model of the system being analyzed.

Data assimilation initially developed in the field of numerical weather prediction. Numerical weather prediction models are equations describing the dynamical behavior of the atmosphere, typically coded into a computer program. In order to use these models to make forecasts, initial conditions are needed for the model that closely resemble the current state of the atmosphere. Simply inserting point-wise measurements into the numerical models did not provide a satisfactory solution. Real world measurements contain errors both due to the **quality** of the instrument and how accurately the **position** of the measurement is known. These errors can cause instabilities in the models that eliminate any level of skill in a forecast. Thus, more sophisticated methods were needed in order to initialize a model using all available data while making sure to maintain stability in the numerical model. Such data typically includes the measurements as well as a previous forecast valid at the same time the measurements are made. If applied iteratively, this process begins to accumulate information from past observations into all subsequent forecasts.

Because data assimilation developed out of the field of numerical weather prediction, it initially gained popularity amongst the meteorologists. In fact, one of the most cited publication in all of the geosciences is an application of data assimilation to reconstruct the observed history of the atmosphere.

Data Assimilation Process

Classically, data assimilation has been applied to chaotic dynamical systems that are too difficult to predict using simple extrapolation methods. The cause of this difficulty is that small changes in initial conditions can lead to large changes in prediction accuracy. This is sometimes known as the butterfly effect – the sensitive dependence on initial conditions in which a small change in one state of a deterministic nonlinear system can result in large differences in a later state.

At any update time, data assimilation usually takes a **forecast** (also known as the **first guess**, or **background** information) and applies a correction to the forecast based on a set of observed data and estimated errors that are present in both the observations and the forecast itself. The difference between the forecast and the observations at that time is called the **departure** or the **innovation** (as it provides new information to the data assimilation process). A weighting factor is applied to the innovation to determine how much of a correction should be made to the forecast based on the new information from the observations. The best estimate of the state of the system based on the correction to the forecast determined by a weighting factor times the innovation is called the **analysis**. In one dimension, computing the analysis could be as simple as forming a weighted average of a forecasted and observed value. In multiple dimensions the problem becomes more difficult. Much of the work in data assimilation is focused on adequately estimating the appropriate weighting factor based on intricate knowledge of the errors in the system.

The measurements are usually made of a real-world system, rather than of the model's incomplete representation of that system, and so a special function called the **observation operator** (usually depicted by *h()* for a nonlinear operator or **H** for its linearization) is needed to map the modeled variable to a form that can be directly compared with the observation.

One of the common mathematical philosophical perspectives is to view data assimilation as a Bayesian estimation problem. From this perspective, the analysis step is an application of Bayes' theorem and the overall assimilation procedure is an example of recursive Bayesian estimation. However, the probabilistic analysis is usually simplified to a computationally feasible form. Advancing the probability distribution in time would be done exactly in the general case by the Fokker–Planck equation, but that is not feasible for high-dimensional systems, so various approximations operating on simplified representations of the probability distributions are used instead. Often the probability distributions are assumed Gaussian so that they can be represented by their mean and covariance, which gives rise to the Kalman filter.

Many methods represent the probability distributions only by the mean and input some pre-calculated covariance. An example of a **direct** (or **sequential**) method to compute this is called optimal statistical interpolation, or simply optimal interpolation (**OI**). An alternative approach is to iteratively solve a cost function that solves an identical problem. These are called **variational** methods, such as 3D-Var and 4D-Var. Typical minimization algorithms are the Conjugate gradient method or the Generalized minimal residual method. The Ensemble Kalman filter is sequential method that uses a Monte Carlo approach to estimate both the mean and the covariance of a Gaussian probability distribution by an ensemble of simulations. More recently, **hybrid** combinations of ensemble approaches and variational methods have become more popular (e.g. they are used for operational forecasts both at the European Centre for Medium-Range Weather Forecasts (ECMWF) and at the NOAA National Centers for Environmental Prediction (NCEP)).

In numerical weather prediction applications, data assimilation is most widely known as a method for combining observations of meteorological variables such as temperature and atmospheric pressure with prior forecasts in order to initialize numerical forecast models.
The atmosphere is a fluid. The idea of numerical weather prediction is to sample the state of the fluid at a given time and use the equations of fluid dynamics and thermodynamics to estimate the state of the fluid at some time in the future. The process of entering observation data into the model to generate initial conditions is called *initialization*. On land, terrain maps available at resolutions down to 1 kilometer (0.6 mi) globally are used to help model atmospheric circulations within regions of rugged topography, in order to better depict features such as downslope winds, mountain waves and related cloudiness that affects incoming solar radiation.The main inputs from country-based weather services are observations from devices (called radiosondes) in weather balloons that measure various atmospheric parameters and transmits them to a fixed receiver, as well as from weather satellites. The World Meteorological Organization acts to standardize the instrumentation, observing practices and timing of these observations worldwide. Stations either report hourly in METAR reports, or every six hours in SYNOP reports. These observations are irregularly spaced, so they are processed by data assimilation and **objective analysis** methods, which perform quality control and obtain values at locations usable by the model's mathematical algorithms.

In 1922, Lewis Fry Richardson published the first attempt at forecasting the weather numerically. Using a hydrostatic variation of Bjerknes's primitive equations, Richardson produced by hand a 6-hour forecast for the state of the atmosphere over two points in central

Europe, taking at least six weeks to do so. His forecast calculated that the change in surface pressure would be 145 millibars (4.3 inHg), an unrealistic value incorrect by two orders of magnitude. The large error was caused by an imbalance in the pressure and wind velocity fields used as the initial conditions in his analysis, indicating the need for a data assimilation scheme.

Originally "subjective analysis" had been used in which NWP forecasts had been adjusted by meteorologists using their operational expertise. Then "objective analysis" (e.g. Cressman algorithm) was introduced for automated data assimilation. These objective methods used simple interpolation approaches, and thus were 3DDA methods.

Later, 4DDA methods, called "nudging", were developed, such as in the MM5 model. They are based on the simple idea of **Newtonian relaxation** (the 2nd axiom of Newton). They introduce into the right part of dynamical equations of the model a term that is proportional to the difference of the calculated meteorological variable and the observed value. This term that has a negative sign keeps the calculated state vector closer to the observations. Nudging can be interpreted as a variant of the Kalman-Bucy filter (a continuous time version of the Kalman filter) with the gain matrix prescribed rather than obtained from covariances.

A major development was achieved by L. Gandin (1963) who introduced the "statistical interpolation" (or "optimal interpolation") method, which developed earlier ideas of **Kolmogorov**. This is a 3DDA method and is a type of regression analysis which utilizes information about the spatial distributions of covariance functions of the errors of the "first guess" field (previous forecast) and "true field". These functions are never known. However, the different approximations were assumed.

The optimal interpolation algorithm is the reduced version of the Kalman filtering (KF) algorithm and in which the covariance matrices are not calculated from the dynamical equations but are pre-determined in advance.

Attempts to introduce the KF algorithms as a 4DDA tool for NWP models came later. However, this was (and remains) a difficult task because the full version requires solution of the enormous number of additional equations (~N*N~10**12, where N=Nx*Ny*Nz is the size of the state vector, Nx~100, Ny~100, Nz~100 – the dimensions of the computational grid). To overcome this difficulty, approximate or suboptimal Kalman filters were developed. These include the Ensemble Kalman filter and the Reduced-Rank Kalman filters (RRSQRT).

Another significant advance in the development of the 4DDA methods was utilizing the optimal control theory (**variational approach**) in the works of Le Dimet and Talagrand (1986), based on the previous works of J.-L. Lions and G. Marchuk, the latter being the first to apply that theory in the environmental modeling. The significant advantage of the variational approaches is that the meteorological fields satisfy the dynamical equations of the NWP model and at the same time they minimize the functional, characterizing their difference from observations. Thus, the problem of constrained minimization is solved. The 3DDA variational methods were developed for the first time by Sasaki (1958).

As was shown by Lorenc (1986), all the above-mentioned 4DDA methods are in some limit equivalent, i.e. under some assumptions they minimize the same cost function. However, in practical applications these assumptions are never fulfilled, the different methods perform differently and generally it is not clear what approach (Kalman filtering or variational) is better. The fundamental questions also arise in application of the advanced DA techniques such as convergence of the computational method to the global minimum of the functional to be minimised. For instance, cost function or the set in which the solution is sought can be not convex. The 4DDA method which is currently most successful is hybrid incremental 4D-Var, where an ensemble is used to augment the climatological background error covariances at the start of the data assimilation time window, but the background error covariances are evolved during the time window by a simplified version of the NWP forecast model. This data assimilation method is used operationally at forecast centres such as the Met Office.

Cost function

The process of creating the analysis in data assimilation often involves minimization of a cost function. A typical cost function would be the sum of the squared deviations of the analysis values from the observations weighted by the accuracy of the observations, plus the sum of the squared deviations of the forecast fields and the analyzed fields weighted by the accuracy of the forecast. This has the effect of making sure that the analysis does not drift too far away from observations and forecasts that are known to usually be reliable.]

3D-Var

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + (\mathbf{y} - H[\mathbf{x}])^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{y} - H[\mathbf{x}]),$$

where $\mathbf{B}$ denotes the background error covariance, $\mathbf{R}$ the observational error covariance.

$$\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) - 2H^T\mathbf{R}^{-1}(\mathbf{y} - H[\mathbf{x}])$$

4D-Var

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + \sum_{i=0}^{n}(\mathbf{y}_i - H_i[\mathbf{x}_i])^{\mathrm{T}}\mathbf{R}_i^{-1}(\mathbf{y}_i - H_i[\mathbf{x}_i])$$

provided that H is a linear operator (matrix).

Data assimilation has been used, in the 1980s and 1990s, in several HAPEX (Hydrologic and Atmospheric Pilot Experiment) projects for monitoring energy transfers between the soil, vegetation and atmosphere. For instance:

- the "Alpilles-ReSeDA" (Remote Sensing Data Assimilation) experiment, a European project

Data assimilation methods are currently also used in other environmental forecasting problems, e.g. in hydrological forecasting. Bayesian networks may also be used in a data assimilation approach to assess natural hazards such as landslides.
Data assimilation is a part of the challenge for every forecasting problem. The existing data assimilation methods such as many variants of ensemble Kalman filters and variational methods, well established with linear or near-linear models, are being assessed on non-linear models, as well as many new methods are being developed e.g. particle filters for high-dimensional problems, hybrids data assimilation methods.

Case study
The Flosolver division at National Aerospace Laboratories (NAL) has developed a **GCM code** called as **VARSHA**. The initialisation of this forecasting system is presently done with the NCEP data. The weather being chaotic dynamical system these initial conditions have to be very accurate. In this the data assimilation plays a vital role in obtaining accurate initial conditions. The aim of the present work was to develop data assimilation system for VARSHA code of NAL for improving its weather forecast. This report presents the work done in this direction under the NMITLI project Mesoscale modelling for monsoon related predictions - Phase II, Data Assimilation for better weather forecast [4].

The 4DVAR and EnKF are the advanced data assimilation systems presently under lot of study. 4D VAR represents the variational approach and EnKF represents ensemble approach. 4DVar has been used in practical applications at ECMWF. It has been studied extensively by many people. The EnKF since its introduction by Evensen has been a subject of lot of study. EnKF has been successfully applied to extensive number of problems. The method is simple conceptually and in implementation. The EnKF unlike variational approach does not require tangent linear model and adjoint equations. The memory requirement is also quite manageable. Hence we decided on using EnKF in our work.

The Flosolver weather forecast code VARSHA uses initial conditions obtained from NCEP. The NCEP keeps publishing this data on a regular basis. In this project it is sought to develop tools so that VARSHA can be used to obtain initial conditions. This helps in assimilating more the observational data that is generated in India and the data collected from elsewhere in the world as well. Hence the project was envisaged to develop a data assimilation system for the

VARSHA code in the Flosolver division of National Aerospace Laboratories, Bangalore. The deliverables were planned as,

I At the end of one year an indigenously developed Data Assimilation (DA) code working on a model problem.
II At the end of two years DA code will be ready (April 2009), which will be able to assimilate data in the VARSHA code.

Ensemble Kalman Filter (EnKF)

As mentioned earlier, based on the literature studies and information collection from various data assimilation centres we chose EnKF as the technique to be employed for data assimilation in our work. The algorithm is briefly explained here. For complete details one can refer to Evensen's papers in the reference section [5].

The analysis step involved in the EnKF is given by,

$$\Psi^a = \Psi^f + K\left(d - H\Psi^f\right)$$

$$K = C^f_{\psi\psi} + H^T\left(HC^f_{\psi\psi}H^T + C_{\varepsilon\varepsilon}\right)^{-1}$$

where,

Ψ = state vector

$C^f_{\psi\psi}$ = forecast error covariance matrix

$C_{\varepsilon\varepsilon}$ = measurement error covariance matrix

The superscript a represents analysis, f represents forecast. The analysis is implemented member by member in an ensemble of members. The covariance matrices in the above equations are evaluated by Monte Carlo estimates.

A = ensemble member & state vector matrix

$= (\Psi_1, \Psi_2, \ldots \Psi_N) \in R^{n \times N}$

A is a $n \times N$ rectangular matrix

A′ = ensemble perturbation matrix which is obtained by subtracting mean from each element of A

The consistent Monte-Carlo estimator for forecast error covariance matrix (obtained from ensemble) is given by,

$$C^e_{\psi\psi} = \frac{A'(A')^T}{N-1}$$

Similarly the measurement error covariance matrix is given by,

$$C^e_{\varepsilon\varepsilon} = \frac{\Upsilon\Upsilon^T}{N-1}$$

where,

$$\Upsilon = \left(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_N\right)$$

is the ensemble of perturbations used for measurements. In terms of perturbation matrices we have finally the EnKF analysis step as,

$$A^a = A^f + A'A'^T H^T \left(HA'A'^T H^T + \Upsilon\Upsilon^T\right)^{-1} D' \quad \text{where,}$$
$$D' = \text{matrix of innovation vectors}$$

Solution of the above equation will involve computation of following matrices:

i. $A' = A - \overline{A} = A(I - 1_N)$

A is the matrix containing state vectors corresponding to each ensemble member.

ii. HA – Forecast or predicted observations

Here H is the measurement operator.

iii. $D' = D - HA$ - innovation vector

D is a matrix containing vector of observations **d**.

iv. HA' – forecasted observations of perturbations.

The main step in analysis equation is calculation of inverse for the matrix,

$$\left(HA'A'^T H^T + \Upsilon\Upsilon^T\right)$$

The inverse of above matrix is computed by using singular value decomposition (SVD). We can rewrite the matrix to be inverted as

$$\left(HA'A'^T H^T + \gamma\gamma^T\right)^{-1} = (HA' + \gamma)(HA' + \gamma)^T$$

This involves assumption of uncorrelated forecast and observation errors. Using SVD the above equation can be written as

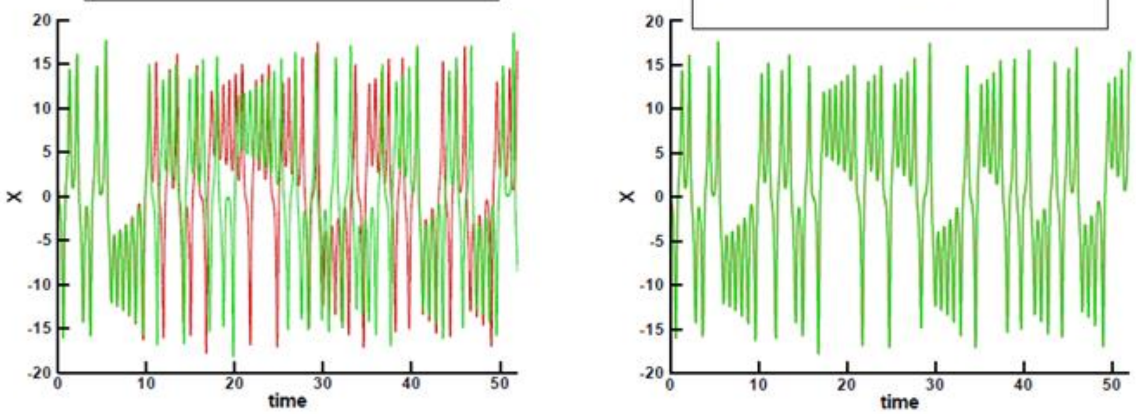
$$(HA' + \gamma)(HA' + \gamma)^T = (U\Sigma V^T)(U\Sigma V^T)^T = U\Sigma\Sigma^T U^T$$

where U –left Eigen vector, V- Right Eigen vector and Σ- contains Eigen vectors on diagonal. From above equation it is easier to see that now inverse can be easily computed. This is the most crucial part of Kalman update equation. In most practical cases, the rank of the matrix can be N (no. Of ensemble members) or less i.e., rank deficiency can cause troubles in finding inverse. In such case we calculate pseudo inverse, again using DA code (SVD-DA to NWP problems along with VARSHA code. [4,5]. (Fig 4.8).

Fig 4.8

Fig. (1) Plot of X Vs time for reference and perturbed initial conditions. Green represents perturbed and red represents reference

Fig. (2) Plot of X Vs time for reference and EnKF. Green represents EnKFand red represents reference. Notice that red and green are almost overlapping here.



perturb them. These values are then used as observations to correct the perturbed run using EnKF. The Fig (2) shows the same plot but in this case the EnKF has been applied, i.e., data assimailation is carried out, to the perturbed trajectory so that we will be able to track the reference trajectory. It is very evident from the figure, the reference and EnKF are coinciding and hence the EnKF has been very successful in tracking the reference solution.

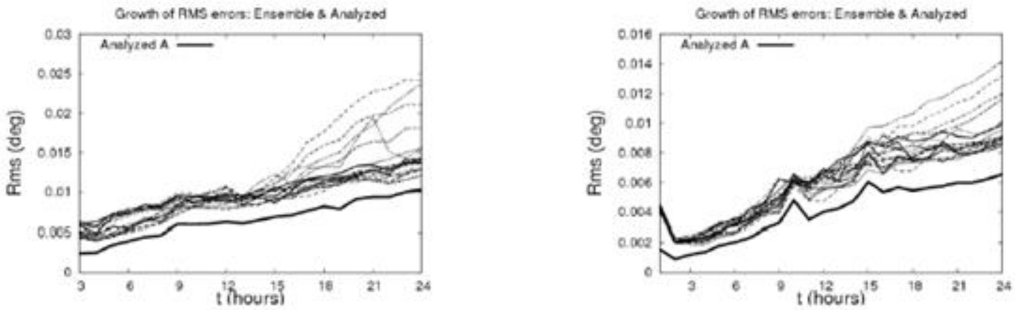
Fig 4.9 Application of DA code (SVD-DA) to NWP problem aling with VARSHA code [4]

Following parameters have been used in the present study.

State size, n = 131072

No. Of observations, m = 8192

Ensemble size, N = 16



Growth of RMS errors **(level 1)** for the ensemble members with respect to the reference run and the analyzed state (with data assimilation).

Growth of RMS errors **(full grid)** for the ensemble members with respect to the reference run and the analyzed state (with data assimilation).

Other uses include trajectory estimation for the Apollo program, GPS, and atmospheric chemistry.

4-3-2 Computations and CFD

An atmospheric model is a computer program that produces meteorological information for future times at given locations and altitudes. Within any modern model is a set of equations, known as the primitive equations, used to predict the future state of the atmosphere. These equations—along with the ideal gas law—are used to evolve the density, pressure, and potential temperature scalar fields and the air velocity (wind) vector field of the atmosphere through time. Additional transport equations for **pollutants** and other aerosols are included in some primitive-equation high-resolution models as well. The equations used are nonlinear partial differential equations which are impossible to solve exactly through analytical methods, with the exception of a few idealized cases. Therefore, numerical methods obtain approximate solutions[1]. Different models use different solution methods: some global models and almost all regional models use finite difference methods (Computational Fluid Dynamic) for all three spatial dimensions, while other global models and a few regional models use spectral methods for the horizontal dimensions and finite-difference methods in the vertical.

These equations are initialized from the analysis data and rates of change are determined (4-3-1). These rates of change predict the state of the atmosphere a short time into the future; the time increment for this prediction is called a ***time step***. This future atmospheric state is then used as the starting point for another application of the predictive equations to find new rates of change, and these new rates of change predict the atmosphere at a yet further time step into the future. This time stepping is repeated until the solution reaches the desired forecast time. The length of the time step chosen within the model is related to the distance between the points on the computational grid, and is chosen to maintain numerical stability. Time steps for global models are on the order of tens of minutes, while time steps for regional models are between one and four minutes. The global models are run at varying times into the future. The UKMET Unified Model is run six days into the future, while the European Centre for Medium-Range Weather Forecasts' Integrated Forecast System and Environment Canada's Global Environmental Multiscale Model both run out to ten days into the future, and the Global Forecast System model run by the Environmental Modeling Center is run sixteen days into the future. The visual output produced by a model solution is known as a prognostic chart, or *prog Fig 4.10)*.

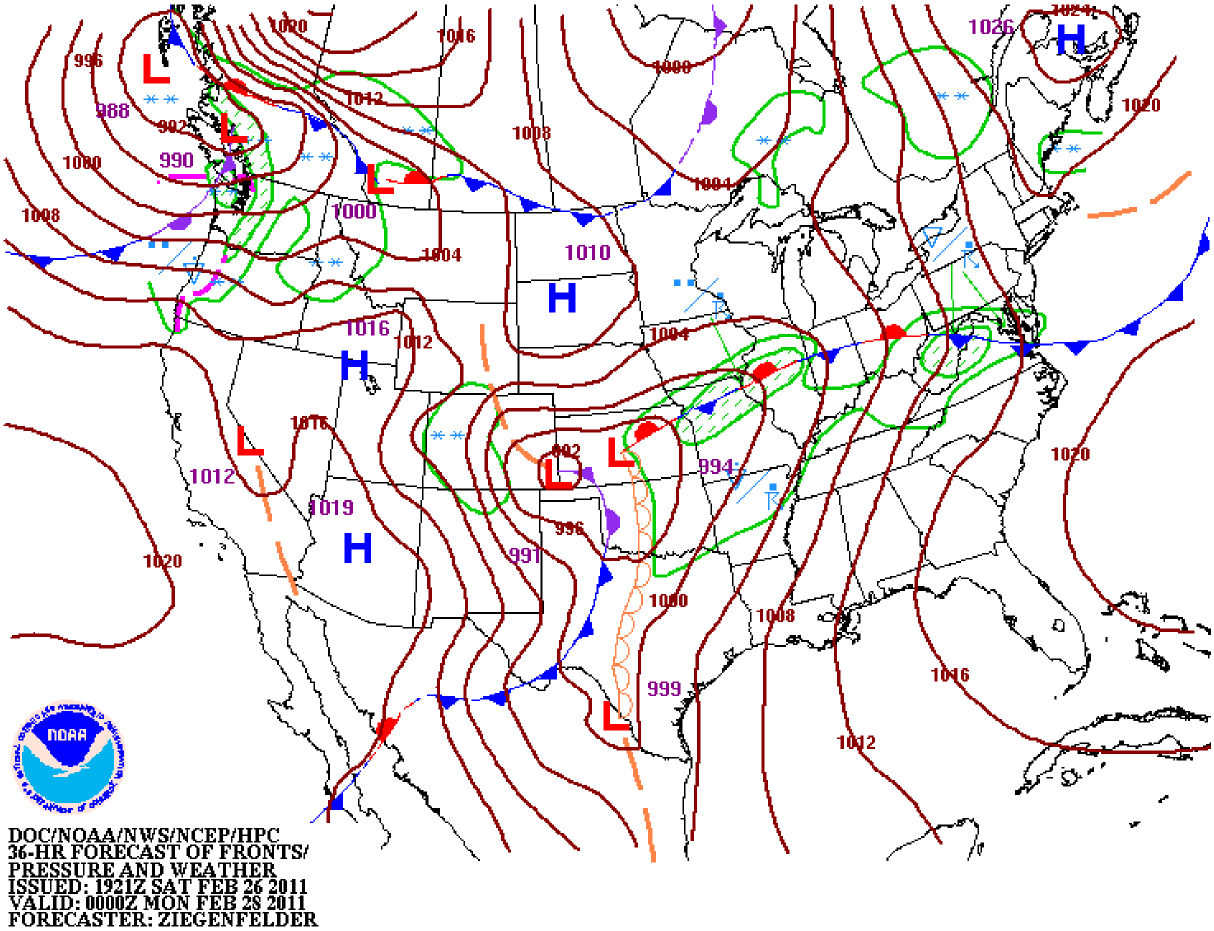


Fig 4.10: A prognostic chart of the of the weather in the United States 36 hours into the future and 96-hour forecast of 850 mbar geopotential height and temperature from the Global Forecast System

Initialization

The process of entering observation data into the model to generate initial conditions is called *initialization*. On land, terrain maps available at resolutions down to 1 kilometer (0.6 mi) globally are used to help model atmospheric circulations within regions of rugged topography, in order to better depict features such as downslope winds, mountain waves and related cloudiness that affects incoming solar radiation. These observations are irregularly spaced, so they are processed by data assimilation and objective analysis methods, which perform quality control and obtain values at locations usable by the model's mathematical algorithms. The data are then used in the model as the starting point for a forecast.

A variety of methods are used to gather observational data for use in numerical models. Sites launch radiosondes in weather balloons which rise through the troposphere and well into the stratosphere. Information from weather satellites is used where traditional data sources are not available. Commerce provides pilot reports along aircraft routes and ship reports along shipping routes.

Research projects use reconnaissance aircraft to fly in and around weather systems of interest, such as tropical cyclones. Reconnaissance aircraft are also flown over the open oceans during the cold season into systems which cause significant uncertainty in forecast guidance, or are expected to be of high impact from three to seven days into the future over the downstream continent. Sea ice began to be initialized in forecast models in 1971. Efforts to involve sea surface temperature in model initialization began in 1972 due to its role in modulating weather in higher latitudes of the Pacific.

Parameterization

Some meteorological processes are too small-scale or too complex to be explicitly included in numerical weather prediction models. *Parameterization* is a procedure for representing these processes by relating them to variables on the scales that the model resolves. For example, the gridboxes in weather and climate models have sides that are between 5 kilometers (3 mi) and 300 kilometers (200 mi) in length. A typical cumulus cloud has a scale of less than 1 kilometer (0.6 mi), and would require a grid even finer than this to be represented physically by the equations of fluid motion. Therefore, the processes that such clouds represent are parameterized, by processes of various sophistication. In the earliest models, if a column of air within a model gridbox was conditionally unstable (essentially, the bottom was warmer and moister than the top) and the water vapor content at any point within the column became saturated then it would be overturned (the warm, moist air would begin rising), and the air in that vertical column mixed. More sophisticated schemes recognize that only some portions of the box might convect and that entrainment and other processes occur. Weather models that have gridboxes with sizes between 5 and 25 kilometers (3 and 16 mi) can explicitly represent convective clouds, although they need to parameterize cloud microphysics which occur at a smaller scale. The formation of large-scale (stratus-type) clouds is more physically based; they form when the relative humidity reaches some prescribed value. Sub-grid scale processes need to be taken into account. Rather than assuming that clouds form at 100% relative humidity, the cloud fraction can be related to a critical value of relative humidity less than 100%, reflecting the sub grid scale variation that occurs in the real world.

The amount of solar radiation reaching the ground, as well as the formation of cloud droplets occur on the molecular scale, and so they must be parameterized before they can be included in the model. Atmospheric drag produced by mountains must also be parameterized, as the limitations in the resolution of elevation contours produce significant underestimates of the drag. This method of parameterization is also done for the surface flux of **energy** between the ocean and the atmosphere, in order to determine realistic sea surface temperatures and type of sea ice found near the ocean's surface. Sun angle as well as the impact of multiple cloud layers is taken into account. Soil type, vegetation type, and soil moisture all determine how much radiation goes into warming and how much moisture is drawn up into the adjacent atmosphere, and thus it is important to parameterize their contribution to these processes.

Within air quality models, parameterizations take into account atmospheric emissions from multiple relatively tiny sources (e.g. roads, fields, factories) within specific grid boxes.

Domains

The horizontal domain of a model is either *global*, covering the entire Earth, or *regional*, covering only part of the Earth. Regional models (also known as *limited-area* models, or LAMs) allow for the use of finer grid spacing than global models because the available computational resources are focused on a specific area instead of being spread over the globe. This allows regional models to resolve explicitly smaller-scale meteorological phenomena that cannot be represented on the coarser grid of a global model. Regional models use a global model to specify conditions at the edge of their domain (boundary conditions) in order to allow systems from outside the regional model domain to move into its area. Uncertainty and errors within regional models are introduced by the global model used for the boundary conditions of the edge of the regional model, as well as errors attributable to the regional model itself.

Horizontal coordinates

Horizontal position may be expressed directly in geographic coordinates (latitude and longitude) for global models or in a map projection planar coordinates for regional models. The German weather service is using for its global ICON model (icosahedral non-hydrostatic global circulation model) a grid based on a regular icosahedron. Basic cells in this grid are triangles instead of the four corner cells in a traditional latitude-longitude grid. The advantage is that, different from a latitude-longitude cells are everywhere on the globe the same size. Disadvantage is that equations in this non rectangular grid are more complicated.

Vertical coordinates

The vertical coordinate is handled in various ways. Lewis Fry Richardson's 1922 model used geometric height as the vertical coordinate. Later models substituted the geometric coordinate with a pressure coordinate system, in which the geopotential heights of constant-pressure surfaces become dependent variables, greatly simplifying the primitive equations. This correlation between coordinate systems can be made since pressure decreases with height through the Earth's atmosphere. The first model used for operational forecasts, the single-layer barotropic model, used a single pressure coordinate at the 500-millibar (about 5,500 m (18,000 ft)) level, and thus was essentially two-dimensional. High-resolution models—also called mesoscale models—such as the Weather Research and Forecasting model tend to use normalized pressure coordinates referred to as sigma coordinates. This coordinate system receives its name from the independent variable used to scale atmospheric pressures with respect to the pressure at the surface, and in some cases also with the pressure at the top of the domain.

4-3-3 MOS

The output of forecast models based on atmospheric dynamics is unable to resolve some details of the weather near the Earth's surface. As such, a statistical relationship between the output of a numerical weather model and the ensuing conditions at the ground was developed in the 1970s and 1980s, known as model output statistics (MOS).

Because forecast models based upon the equations for atmospheric dynamics do not perfectly determine weather conditions, statistical methods have been developed to attempt to correct the forecasts. Statistical models were created based upon the three-dimensional fields produced by numerical weather models, surface observations and the climatological conditions for specific locations. These statistical models are collectively referred to as model output statistics (MOS), and were developed by the National Weather Service for their suite of weather forecasting models in the late 1960s.

Model output statistics differ from the *perfect prog* technique, which assumes that the output of numerical weather prediction guidance is perfect. MOS can correct for local effects that cannot be resolved by the model due to insufficient grid resolution, as well as model biases. Because MOS is run after its respective global or regional model, its production is known as post-processing. Forecast parameters within MOS include maximum and minimum temperatures, percentage chance of rain within a several hour period, precipitation amount expected, chance that the precipitation will be frozen in nature, chance for thunderstorms, cloudiness, and surface winds.

4-3-4 Equations in weather forecasting

The atmosphere is a fluid. As such, the idea of numerical weather prediction is to sample the state of the fluid at a given time and use the equations of fluid dynamics and thermodynamics to estimate the state of the fluid at some time in the future.

In physics and engineering, **fluid dynamics** is a subdiscipline of fluid mechanics that describes the flow of fluids—liquids and gases. The foundational axioms of fluid dynamics are the conservation laws, specifically, conservation of mass, conservation of linear momentum, and conservation of energy (also known as First Law of Thermodynamics). These are based on classical mechanics and are modified in quantum mechanics and general relativity. They are expressed using the Reynolds transport theorem.

A set of equations, known as the primitive equations, used to predict the future state of the atmosphere. These equations (the primitive equations that are still in use in numerical weather prediction and climate modeling,) —along with the ideal gas law—are used to evolve the density, pressure, and potential temperature scalar fields and the air velocity (wind) vector field of the atmosphere through time.

The **primitive equations** are a set of nonlinear differential equations that are used to approximate global atmospheric flow and are used in most atmospheric models. They consist of three main sets of balance equations:

1. A *continuity equation*: Representing the conservation of mass.
2. *Conservation of momentum*: Consisting of a form of the Navier–Stokes equations that describe hydrodynamical flow on the surface of a sphere under the assumption that vertical motion is much smaller than horizontal motion (hydrostasis) and that the fluid layer depth is small compared to the radius of the sphere
3. A *thermal energy equation*: Relating the overall temperature of the system to heat sources and sinks

The primitive equations may be linearized to yield Laplace's tidal equations, an eigenvalue problem from which the analytical solution to the latitudinal structure of the flow may be determined.
In general, nearly all forms of the primitive equations relate the five variables *u*, *v*, ω, *T*, *W*, and their evolution over space and time respectively:

- The equations were first written down by Vilhelm Bjerknes, who was physicist and meteorologist (1951).

Definitions

- u is the zonal velocity (velocity in the east/west direction tangent to the sphere)
- v is the meridional velocity (velocity in the north/south direction tangent to the sphere)
- ω is the vertical velocity in isobaric coordinates
- T is the temperature
- Φ is the geopotential
- f is the term corresponding to the Coriolis force, and is equal to $2\Omega\sin(\phi)$, where Ω is the angular rotation rate of the Earth ($2\pi/24$ radians per sidereal hour), and ϕ is the latitude
- R is the gas constant
- p is the pressure
- c_p is the specific heat on a constant pressure surface
- J is the heat flow per unit time per unit mass
- W is the precipitable water
- Π is the Exner function
- θ is the potential temperature
- η is the Absolute vorticity

some equations in weather forecasting:

Primitive equations using sigma coordinate system, polar stereographic projection

According to the *National Weather Service Handbook No. 1 – Facsimile Products*, the primitive equations can be simplified into the following equations:

- Zonal wind:

$$\frac{\partial u}{\partial t} = \eta v - \frac{\partial \Phi}{\partial x} - c_p \theta \frac{\partial \pi}{\partial x} - z \frac{\partial u}{\partial \sigma} - \frac{\partial (\frac{u^2+v^2}{2})}{\partial x}$$

- Meridional wind:

$$\frac{\partial v}{\partial t} = -\eta \frac{u}{v} - \frac{\partial \Phi}{\partial y} - c_p \theta \frac{\partial \pi}{\partial y} - z \frac{\partial v}{\partial \sigma} - \frac{\partial (\frac{u^2+v^2}{2})}{\partial y}$$

- Temperature:

$$\frac{\delta T}{\partial t} = \frac{\partial T}{\partial t} + u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} + w \frac{\partial T}{\partial z}$$

The first term is equal to the change in temperature due to incoming solar radiation and outgoing longwave radiation, which changes with time throughout the day. The second, third, and fourth terms are due to advection. Additionally, the variable *T* with subscript is the change in temperature on that plane. Each *T* is actually different and related to its respective plane. This is divided by the distance between grid points to get the change in temperature with the change in distance. When multiplied by the wind velocity on that plane, the units kelvins per meter and meters per second give kelvins per second. The sum of all the changes in temperature due to motions in the *x*, *y*, and *z* directions give the total change in temperature with time.

- Precipitable water:

$$\frac{\delta W}{\partial t} = u\frac{\partial W}{\partial x} + v\frac{\partial W}{\partial y} + w\frac{\partial W}{\partial z}$$

This equation and notation works in much the same way as the temperature equation. This equation describes the motion of water from one place to another at a point without taking into account water that changes form. Inside a given system, the total change in water with time is zero. However, concentrations are allowed to move with the wind.

- Pressure thickness:

$$\frac{\partial}{\partial t}\frac{\partial p}{\partial \sigma} = u\frac{\partial}{\partial x}x\frac{\partial p}{\partial \sigma} + v\frac{\partial}{\partial y}y\frac{\partial p}{\partial \sigma} + w\frac{\partial}{\partial z}z\frac{\partial p}{\partial \sigma}$$

These simplifications make it much easier to understand what is happening in the model. Things like the temperature (potential temperature), precipitable water, and to an extent the pressure thickness simply move from one spot on the grid to another with the wind. The wind is forecast slightly differently. It uses geopotential, specific heat, the exner function π, and change in sigma coordinate.

This analytic solution is only possible when the primitive equations are linearized and simplified. Unfortunately many of these simplifications (i.e. no dissipation, isothermal atmosphere) do not correspond to conditions in the actual atmosphere. As a result, a numerical solution which takes these factors into account is often calculated using general circulation models and climate models.

The analytic solution to the linearized primitive equations involves a sinusoidal oscillation in time and longitude, modulated by coefficients related to height and latitude for example:

$$\{u, v, \phi\} = \{\hat{u}, \hat{v}, \hat{\phi}\}e^{i(s\lambda+\sigma t)}$$

Where s and σ are the zonal wave number and angular frequency, respectively. The solution represents atmospheric waves and tides.

4-4 Weather forecastingTechniques

Weather forecasting (formally since the 19th century) is the application of science and technology to predict the conditions of the atmosphere for a given location and time. Weather forecasts are made by collecting quantitative data about the current state of the atmosphere at a given place and using meteorology to project how the atmosphere will change. Once calculated by hand based mainly upon changes in barometric pressure, current weather conditions, and sky condition or cloud cover, weather forecasting now relies on computer-based models that take many atmospheric factors into account.[1] Human input is still required to pick the best possible forecast model to base the forecast upon, which involves pattern recognition skills, teleconnections (Climate anomalies and stationary and non-stationary effects-sea level pressure, sun effects, latitude circles and eddies, ENSO effects in temperature and rainfall,…), knowledge of model performance, and knowledge of model biases. The inaccuracy of forecasting is due to the chaotic (States of dynamical systems are often governed by deterministic laws that are highly sensitive to initial conditions, Edward Lorenz, 2019 mathematician and meteorologist) nature of the atmosphere, the massive computational power required to solve the equations that describe the atmosphere, the error involved in measuring the initial conditions, and an incomplete understanding of atmospheric processes. Hence, forecasts become less accurate as the difference between current time and the time for which the forecast is being made (the *range* of the forecast) increases. The use of ensembles and model consensus help narrow the error and pick the most likely outcome.

There are a variety of end uses to weather forecasts. Weather warnings are important forecasts because they are used to protect life and property. Forecasts based on temperature and precipitation are important to agriculture, and therefore to traders within commodity markets. Temperature forecasts are used by utility companies to estimate demand over coming days. On an everyday basis, people use weather forecasts to determine what to wear on a given day. Since outdoor activities are severely curtailed by heavy rain, snow and wind chill, forecasts can be used to plan activities around these events, and to plan ahead and survive them. In 2009, the US spent $5.1 billion on weather forecasting.

4-4-1- Weather lore

Ancient weather forecasting methods usually relied on observed patterns of events, also termed pattern recognition or signs. For example, it might be observed that if the sunset was particularly red, the following day often (some uncertainty) brought fair weather. This experience accumulated over the generations to produce weather lore. However, not all of these predictions prove reliable, and many of them have since been found not to stand up to rigorous statistical testing. In IRAN's villages people have many experiences of the signs (estimated more than 500 signs [1]) about weather phenomena shuch as cloud patterns, or rising water level in wells or lunar phases or movement of winds relevant to rain events. Understanding local weather patterns, by saying, "When evening comes, you say, 'It will be fair weather, for the sky is red', and in the morning, 'Today it will be stormy, for the sky is red and overcast.' You know how to interpret the appearance of the sky, but you cannot interpret the signs of the times and other characteristics.

The simplest method of forecasting the weather, persistence, relies upon today's conditions to forecast the conditions tomorrow. This can be a valid way of forecasting the weather when it is in a steady state, such as during the summer season in the tropics. This method of forecasting strongly depends upon the presence of a stagnant weather pattern. Therefore, when in a fluctuating weather pattern, this method of forecasting becomes inaccurate. It can be useful in both short range forecasts and long range forecasts.

Along with pressure tendency, the condition of the sky is one of the more important parameters used to forecast weather in mountainous areas. Thickening of cloud cover or the invasion of a higher cloud deck is indicative of rain in the near future. High thin cirrostratus clouds can create halos around the sun or moon, which indicates an approach of a warm front and its associated rain. Morning fog portends fair conditions, as rainy conditions are preceded by wind or clouds that prevent fog formation. The approach of a line of thunderstorms could indicate the approach of a cold front. Cloud-free skies are indicative of fair weather for the near future. A bar can indicate a coming tropical cyclone. The use of sky cover in weather prediction has led to various weather lore over the centuries.

The **analog technique** is a complex way (another type of weather lore) of making a forecast, requiring the forecaster to remember a previous weather event that is expected to be mimicked by an upcoming event. What makes it a difficult technique to use is that there is rarely a perfect analog for an event in the future. Some call this type of forecasting pattern recognition. It remains a useful method of observing rainfall over data voids such as **oceans**, as well as the forecasting of precipitation amounts and distribution in the future. A similar technique is used in medium range forecasting, which is known as teleconnections, when systems in other locations are used to help pin down the location of another system within the surrounding regime. An example of teleconnections are by using El Niño-Southern Oscillation (ENSO) related phenomena that described in 4-4-5 section.

4-4-2- Simple technology

It was not until the invention of the electric telegraph in 1835 that the modern age of weather forecasting began. Before that, the fastest that distant weather reports could travel was

around 160 kilometres per day (100 mi/d), but was more typically 60–120 kilometres per day (40–75 mi/day) (whether by land or by sea). By the late 1840s, the telegraph allowed reports of weather conditions from a wide area to be received almost instantaneously, allowing forecasts to be made from knowledge of weather conditions further upwind. A storm in 1859 that caused the loss of the *Royal Charter* inspired FitzRoy to develop charts to allow predictions to be made, which he called *"forecasting the weather"*, thus coining the term "weather forecast". Fifteen land stations were established to use the telegraph to transmit to him daily reports of weather at set times leading to the first gale warning service. Using photography, barometer and ,… are other simple technologies that maybe useful.

Measurements of barometric pressure and the pressure tendency (the change of pressure over time) have been used in forecasting since the late 19th century. The larger the change in pressure, especially if more than 3.5 hPa (2.6 mmHg), the larger the change in weather can be expected. If the pressure drop is rapid, a low pressure system is approaching, and there is a greater chance of rain. Rapid pressure rises are associated with improving weather conditions, such as clearing skies.

The low temperature forecast for the current day is calculated using the lowest temperature found between 7 pm that evening through 7 am the following morning. So, in short, today's forecasted low is most likely tomorrow's low temperature.

4-4-3- Advanced technology

The forecasting of the weather within the next six hours is often referred to as **nowcasting**. In this time range it is possible to forecast **smaller features** such as individual showers and thunderstorms with reasonable accuracy, as well as other features too small to be resolved by a computer model such as numerical weather prediction (NWP) models running over longer forecast periods.

So, **Nowcasting** is weather forecasting on a very short term mesoscale period of up to 2 hours according to the World Meteorological Organization and up to six hours according to other authors in the field. This forecast is an extrapolation in time of known weather parameters, including those obtained by means of **remote sensing**, using techniques that take into account a possible evolution of the air mass. This type of forecast therefore includes details that cannot be solved by NWP techniques running over longer forecast periods.

A human given the latest **radar**, **satellite** and observational data will be able to make a better analysis of the small scale features present and so will be able to make a more accurate forecast for the following few hours. However, there are now expert systems using those data and **mesoscale numerical model** to make better extrapolation, including evolution of those features in time. Accuweather Co. is known for a Minute-Cast, which is a minute-by-minute precipitation forecast for the next two hours.

Nowcasting in meteorology uses surface weather station data, wind profiler data, and any other weather data available to initialize the current weather. Weather radar echoes and **satellite** data, giving cloud coverage, are particularly important in nowcasting because they are very detailed and pick out the size, shape, intensity, speed and direction of movement of individual features of weather on a continuous basis and a vastly better resolution than surface weather stations.

This used to be a simple extrapolation by a forecaster for the following few hours. But with the development of mesoscale numerical weather models, these information can be ingested into an expert system to produce a much better forecast combining numerical weather prediction and local effects not normally possible to be known beforehand. Different research groups, public and private, have developed such programs.

For instance, the French weather service, Météo-France, is using a software, named *ASPIC* to extrapolate to a fine scale the areas of precipitation. Other examples are *AutoNowcaster* which has been developed by UCAR to predict short term motion and evolution of thunderstorms, and private firms like ClimaCell using its proprietary HyperCast software for nowcasting precipitation type and intensity at 300-500 m geospatial resolution.

Data extrapolation, including development or dissipation, can be used to find the likely location of a moving weather system. The intensity of rainfall from a particular cloud or group of clouds can be estimated, giving a very good indication as to whether to expect flooding, the swelling of a river etc. Depending on the area of built-up space, drainage and land-use in general, a forecast warning may be issued.

The short term forecast is as old as weather forecasting itself. During the nineteenth century, the first modern meteorologists were using extrapolation methods for predicting the movement of low pressure systems and anticyclones on surface maps. The researchers subsequently applied the laws of fluid dynamics to the atmosphere and developed the NWP as we know it today. However, the data resolution and parameterization of meteorological primitive equations still leave **uncertainty** about the small-scale projections, in time and space.

The arrival of remote sensing means, such as radar and satellite, and more rapid development of the computer, greatly help to fill that gap. For instance, digital radar systems made it possible to track thunderstorms, providing users with the ability to acquire detailed information of each storm tracked, since the late 1980s. They are first identified by matching precipitation raw data to a set of preprogrammed characteristics into the system, including signs of organization in the horizontal and continuity in the vertical. Once the thunderstorm cell is identified, speed, distance covered, direction, and Estimated Time of Arrival (ETA) are all tracked and recorded to be utilized later.

In 2017, the arrival of passive sensing means, such as wireless networks, helped progress nowcasting even further. It became possible to receive inputs every minute and achieve greater accuracy in short-term forecasting.

Several countries have developed nowcasting programs as previously mentioned. The World Meteorological Organization (WMO) supports these efforts and held test campaigns of such systems at various occasions. For example, during the Olympic Games in Sydney and Beijing, several countries were invited to use their software to support the Games.

Several scientific conferences addressing the topic. In 2009, WMO has even organized a symposium devoted to Nowcasting.

4-4-4-Forecast models

In the past, the human forecaster was responsible for generating the entire weather forecast based upon available observations. Today, hydrologists, input is generally confined to choosing a model (such as **NWP** or **GCM**) based on various parameters, such as model biases and performance. Using a consensus of forecast models, as well as **ensemble** members of the various models, can help reduce forecast error.

However, regardless how small the average error becomes with any individual system, large errors within any particular piece of guidance are still possible on any given model run. Hydrologists and meteorologists, are required to interpret the model data into weather forecasts that are understandable to the end user. They can use knowledge of **local effects** that may be too small in size to be resolved by the model to add information to the forecast. While increasing accuracy of forecast models implies that they may no longer be needed in the forecast process at some point in the future, there is currently still a need for meteorologists intervention.

4-4-4-1-Ensemble forecasting

Starting in the 1990s, **model ensemble forecasts** have been used to help define the forecast uncertainty and to extend the window in which numerical weather forecasting is viable farther into the future than otherwise possible (Fig. 4-11).

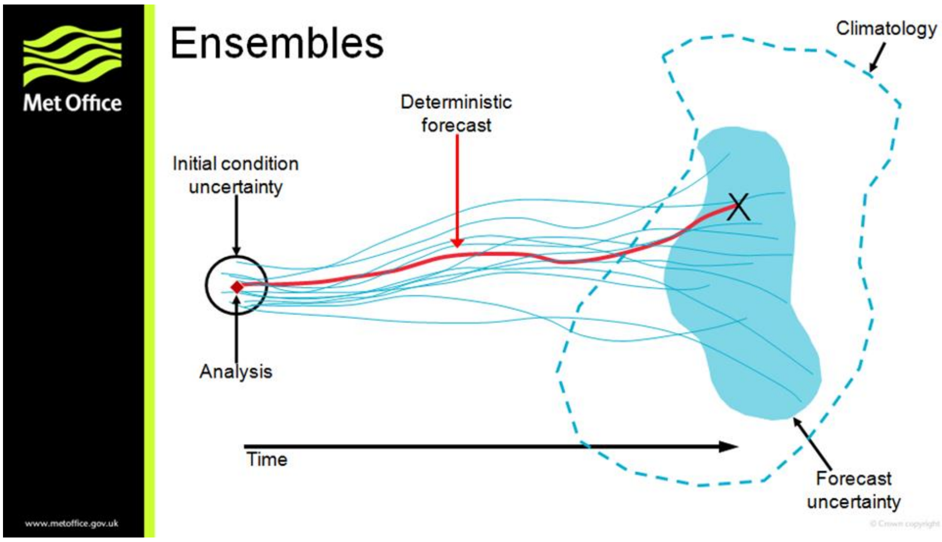


Fig. 4-11 A schematic illustration of an ensemble forecast

Ensemble forecasting is a method used in numerical weather prediction. Instead of making a single forecast of the most likely weather, a set (or ensemble) of forecasts is produced. This set of forecasts aims to give an indication of the range of possible future states of the atmosphere. Ensemble forecasting is a form of Monte Carlo analysis. The multiple simulations are conducted to account for the two usual sources of uncertainty in forecast models: (1) the errors introduced by the use of imperfect initial conditions, amplified by the chaotic nature of the evolution equations of the atmosphere, which is often referred to as sensitive dependence on initial conditions; and (2) errors introduced because of imperfections in the model formulation, such as the approximate mathematical methods to solve the equations. Ideally, the verified future atmospheric state should fall within the predicted ensemble spread, and the amount of spread should be related to the uncertainty (error) of the forecast. In general, this approach can be used to make probabilistic forecasts of any dynamical system, and not just for weather prediction.

Today ensemble predictions are commonly made at most of the major operational weather prediction facilities worldwide, including:

- National Centers for Environmental Prediction (NCEP of the US)
- European Centre for Medium-Range Weather Forecasts (ECMWF)
- United Kingdom Met Office
- Météo-France
- Environment Canada
- Japan Meteorological Agency
- Bureau of Meteorology (Australia)
- China Meteorological Administration (CMA)
- Korea Meteorological Administration
- CPTEC (Brazil)
- Ministry of Earth Sciences (IMD, IITM & NCMRWF) (India)

Experimental ensemble forecasts are made at a number of universities, such as the University of Washington, and ensemble forecasts in the US are also generated by the US Navy and Air Force. There are various ways of viewing the data such as spaghetti plots, *ensemble means* or *Postage Stamps* where a number of different results from the models run can be compared.

As proposed by Edward Lorenz in 1963, it is impossible for long-range forecasts—those made more than two weeks in advance—to predict the state of the atmosphere with any degree of skill owing to the chaotic nature of the fluid dynamics equations involved. Furthermore, existing observation networks have limited spatial and temporal resolution (for example, over large bodies of water such as the Pacific Ocean), which introduces uncertainty into the true initial state of the atmosphere. While a set of equations, known as the **Liouville equations,** exists to determine the initial uncertainty in the model initialization, the equations are too complex to run in real-time, even with the use of supercomputers. The practical importance of ensemble forecasts derives from the fact that in a chaotic and hence nonlinear system, the rate of growth of forecast error is dependent on starting conditions. An ensemble forecast therefore provides a prior estimate of state-dependent predictability, i.e. an estimate of the types of weather that might occur, given inevitable uncertainties in the forecast initial conditions and in the accuracy of the computational representation of the equations. These uncertainties limit forecast model accuracy to about six days into the future. The first operational ensemble forecasts were produced for sub-seasonal timescales in 1985. However, it was realised that the philosophy underpinning such forecasts was also relevant on shorter timescales – timescales where predictions had previously been made by purely deterministic means.

Edward Epstein recognized in 1969 that the atmosphere could not be completely described with a single forecast run due to inherent uncertainty, and proposed a stochastic dynamic model that produced means and variances for the state of the atmosphere. Although these Monte Carlo simulations showed skill, in 1974 Cecil Leith revealed that they produced adequate forecasts only when the ensemble probability distribution was a representative sample of the probability distribution in the atmosphere. It was not until 1992 that ensemble forecasts began being prepared by the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Centers for Environmental Prediction (NCEP).

There are two main sources of uncertainty that must be accounted for when making an ensemble weather forecast: initial condition uncertainty and model uncertainty:

Initial condition uncertainty

Initial condition uncertainty arises due to errors in the estimate of the starting conditions for the forecast, both due to limited observations of the atmosphere, and uncertainties involved in using indirect measurements, such as satellite data, to measure the state of atmospheric variables. Initial condition uncertainty is represented by perturbing the starting conditions between the different ensemble members. This explores the range of starting conditions consistent with our knowledge of the current state of the atmosphere, together with its past evolution. There are a number of ways to generate these initial condition perturbations. The ECMWF model, the Ensemble Prediction System (EPS), uses a combination of singular vectors and an ensemble of data assimilations (EDA) to simulate the initial probability density. The singular vector perturbations are more active in the extra-tropics, while the EDA perturbations are more active in the tropics. The NCEP ensemble, the Global Ensemble Forecasting System, uses a technique known as vector breeding.

Model uncertainty

Model uncertainty arises due to the limitations of the forecast model. The process of representing the atmosphere in a computer model involves many simplifications such as the development of parametrisation schemes, which introduce errors into the forecast. Several techniques to represent model uncertainty have been proposed. In here 3 methods:

1-Perturbed parameter schemes

When developing a parametrisation scheme, many new parameters are introduced to represent simplified physical processes. These parameters may be very uncertain. For example, the 'entrainment coefficient' represents the turbulent mixing of dry environmental air into a convective cloud, and so represents a complex physical process using a single number. In a perturbed parameter approach, uncertain parameters in the model's parametrisation schemes are identified and their value changed between ensemble members. While in probabilistic climate modelling, such as climateprediction.net, these parameters are often held constant globally and throughout the integration, in modern numerical weather prediction it is more common to stochastically vary the value of the parameters in time and space. The degree of parameter perturbation can be guided using expert judgement, or by directly estimating the degree of parameter uncertainty for a given model(Fig.4-11).

2-Stochastic parametrisations

A traditional parametrisation scheme seeks to represent the average effect of the sub grid-scale motion (e.g. convective clouds) on the resolved scale state (e.g. the large scale temperature and wind fields). A stochastic parametrisation scheme recognises that there may be many sub-grid scale states consistent with a particular resolved scale state. Instead of predicting the most likely sub-grid scale motion, a stochastic parametrisation scheme represents one possible realisation of the sub-grid. It does this through including random numbers into the equations of motion[6]. This samples from the probability distribution assigned to uncertain processes (Fig. 4-12). Stochastic parametrisations have significantly improved the skill of weather forecasting models, and are now used in operational forecasting centres worldwide. Stochastic parametrisations were first developed at the European Centre for Medium Range Weather Forecasts.

3-Multi model ensembles

When many different forecast models are used to try to generate a forecast, the approach is termed **multi-model ensemble forecasting**. This method of forecasting can improve forecasts when compared to a single model-based approach. When the models within a multi-model ensemble are adjusted for their various biases, this process is known as "**superensemble** forecasting". This type of a forecast significantly reduces errors in model output.

When models of different physical processes are combined, such as combinations of atmospheric, ocean and wave models, the multi-model ensemble is called **hyper-ensemble**.

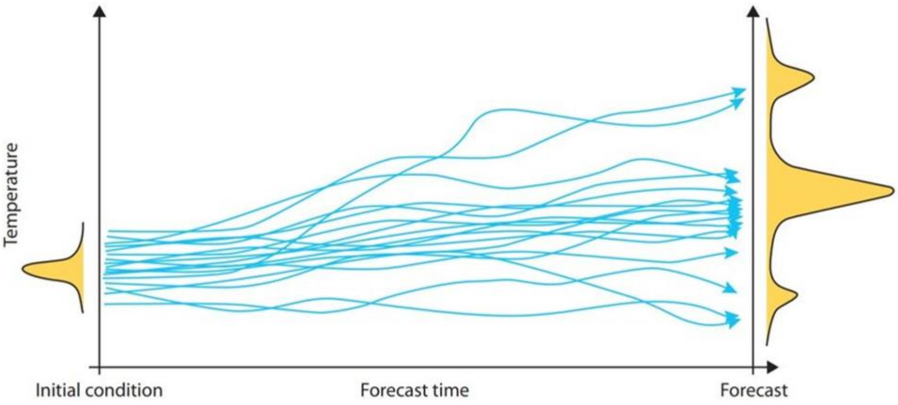


Fig. 4-12 ECMWF ensemble prediction system

Probability assessment

The ensemble forecast is usually evaluated by comparing the average of the individual forecasts for one forecast variable to the observed value of that variable (the "error"). This is combined with consideration of the degree of agreement between various forecasts within the ensemble system, as represented by their overall standard deviation or "spread". Ensemble spread can be visualised through tools such as spaghetti diagrams, which show the dispersion of one quantity on prognostic charts for specific time steps in the future. Another tool where ensemble spread is used is a meteogram, which shows the dispersion in the forecast of one quantity for one specific location. Three methods:

1-Reliability and resolution (calibration and sharpness)

The spread of the ensemble forecast indicates how confident the forecaster can be in his or her prediction. When ensemble spread is small and the forecast solutions are consistent within multiple model runs, forecasters perceive more confidence in the forecast in general. When the spread is large, this indicates more uncertainty in the prediction. Ideally, a spread-skill relationship should exist, whereby the spread of the ensemble is a good predictor of the expected error in the ensemble mean. If the forecast is reliable, the observed state will behave as if it is drawn from the forecast probability distribution. Reliability (or calibration) can be evaluated by comparing the standard deviation of the error in the ensemble mean with the forecast spread: for a reliable forecast, the two should match, both at different forecast lead times and for different locations.

The reliability of forecasts of a specific weather event can also be assessed. For example, if 30 of 50 members indicated greater than 1 cm rainfall during the next 24 h, the probability of exceeding 1 cm could be estimated to be 60%. The forecast would be considered reliable if, considering all the situations in the past when a 60% probability was forecast, on 60% of those occasions did the rainfall actually exceed 1 cm. In practice, the probabilities generated from operational weather ensemble forecasts are not highly reliable, though with a set of past forecasts (*reforecasts* or *hindcasts*) and observations, the probability estimates from the ensemble can be adjusted to ensure greater reliability.

Another desirable property of ensemble forecasts is resolution. This is an indication of how much the forecast deviates from the climatological event frequency – provided that the ensemble is reliable. This forecast quality can also be considered in terms of sharpness, or how small the spread of the forecast is. The key aim of a forecaster should be to maximise sharpness, while maintaining reliability. Forecasts at long leads will inevitably not be particularly sharp (have particularly high resolution), for the inevitable (albeit usually small) errors in the initial condition will grow with increasing forecast lead until the expected difference between two model states is as large as the difference between two random states from the forecast model's climatology.

2-Calibration of ensemble forecasts

If ensemble forecasts are to be used for predicting probabilities of observed weather variables they typically need calibration in order to create unbiased and reliable forecasts. For forecasts of temperature one simple and effective method of calibration is linear regression, often known in this context as Model output statistics. The linear regression model takes the ensemble mean as a predictor for the real temperature, ignores the distribution of ensemble members around the mean, and predicts probabilities using the distribution of residuals from the regression. In this calibration setup the value of the ensemble in improving the forecast is then that the ensemble mean typically gives a better forecast than any single ensemble member would, and not because of any information contained in the width or shape of the distribution of the members in the ensemble around the mean. However, in 2004, a generalisation of linear regression (now known as Nonhomogeneous Gaussian regression) was introduced that uses a linear transformation of the ensemble spread to give the width of the predictive distribution, and it was shown that this can lead to forecasts with higher skill than those based on linear regression alone. This proved for the first time that information in the shape of the distribution of the members of an ensemble around the mean, in this case summarized by the **ensemble spread**, can be used to improve forecasts relative to linear regression. Whether or not linear regression can be beaten by using the ensemble spread in this way varies, depending on the forecast system, forecast variable and lead time.

3-Predicting the size of forecast changes

In addition to being used to improve predictions of uncertainty, the **ensemble spread** can also be used as a predictor for the likely size of changes in the mean forecast from one forecast to the next. This works because, in some ensemble forecast systems, **narrow** ensembles tend to precede small changes in the mean, while **wide** ensembles tend to precede larger changes in the mean. This has applications in the trading industries, for whom understanding the likely sizes of future forecast changes can be important.

Co-ordinated research

Main article: THORPEX Interactive Grand Global Ensemble

The Observing System Research and Predictability Experiment (THORPEX) is a 10-year international research and development programme to accelerate improvements in the accuracy of one-day to two-week high impact weather forecasts for the benefit of society, the economy and the environment. It establishes an organizational framework that addresses weather research and forecast problems whose solutions will be accelerated through international collaboration among academic institutions, operational forecast centres and users of forecast products.

One of its key components is THORPEX Interactive Grand Global Ensemble (TIGGE), a World Weather Research Programme to accelerate the improvements in the accuracy of 1-day to 2 week high-impact weather forecasts for the benefit of humanity. Centralized archives of ensemble model forecast data, from many international centers, are used to enable extensive data sharing and research.

4-4-5- Teleconnections

El Niño (/ɛl ˈniːn.joʊ/; is the warm phase of the El Niño–Southern Oscillation (ENSO) and is associated with a band of warm ocean water that develops in the central and east-central equatorial Pacific (between approximately the International Date Line and 120°W), including the area of the Pacific coast of South America. The ENSO is the cycle of warm and cold sea surface temperature (SST) of the tropical central and eastern Pacific Ocean. El Niño is accompanied by high air pressure in the western Pacific and low air pressure in the eastern Pacific. El Niño phases are known to occur close to four years, however, records demonstrate that the cycles have lasted between two and seven years. During the development of El Niño, rainfall develops between September–November. The cool phase of ENSO is La Niña, with SSTs in the eastern Pacific below average, and air pressure high in the eastern Pacific and low in the western Pacific. The ENSO cycle, including both El Niño and La Niña, causes global changes in temperature and rainfall (Fig. 4-13 and 4-14).

Since tropical sea surface temperatures are predictable up to two years ahead of time, knowledge of teleconnection patterns gives some amount of predictability in remote locations with an outlook sometimes as long as a few seasons. Predicting El Niño, for instance, enables prediction of North American rainfall, snowfall, droughts or temperature patterns with a few weeks to months lead time. In Sir Gilbert Walker's time, A strong El Niño usually meant a weaker Indian monsoon, but this anticorrelation has weakened in the 1980s and 1990s, for controversial reasons.

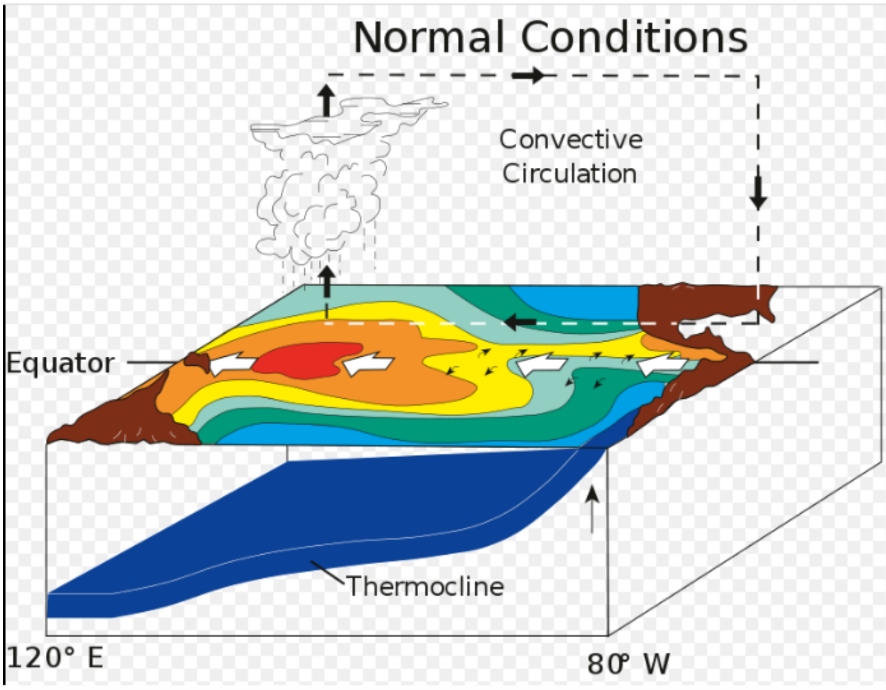


Fig: 4-13 Normal Pacific pattern: Warm pool in the west drives deep atmospheric convection. Local winds cause nutrient-rich cold water to upwell along the South American coast. (NOAA / PMEL / TAO).

ENSO normal state. Normal equatorial winds warm as they flow westward across the Pacific. Cold water is pulled up along west coast of South America. Warming water is pushed toward west side of Pacific. Sea surface is warm in the west. Hot air rises in western Pacific, travels eastward and cool air descends on South America.

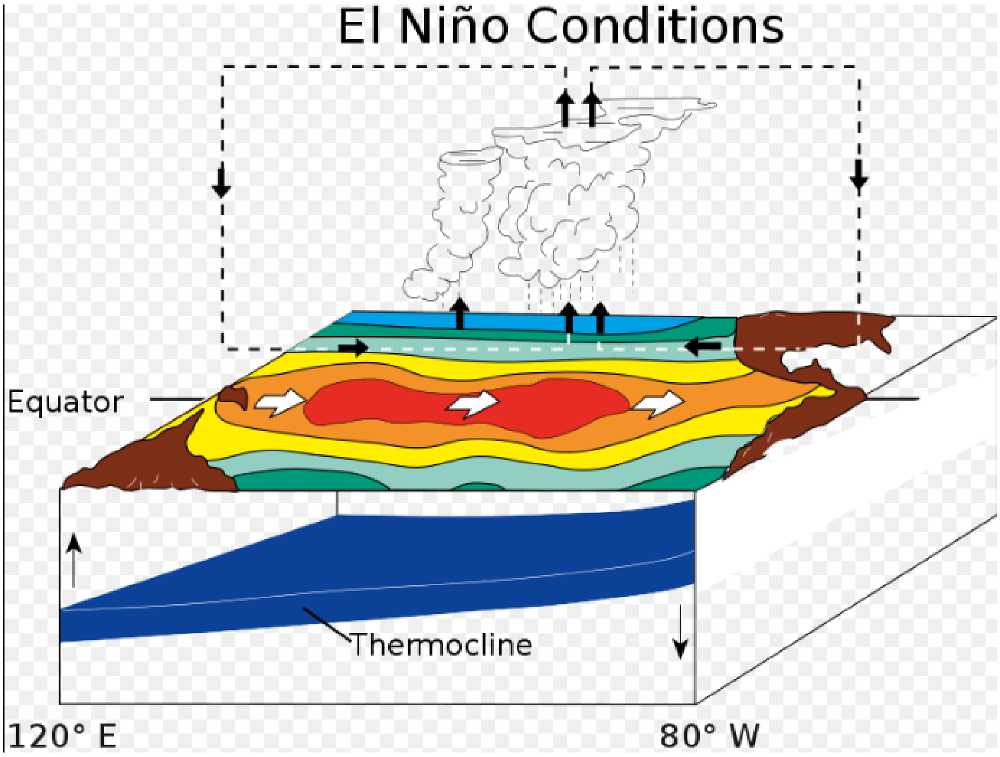


Fig 4-14 El Niño conditions: warm water and atmospheric convection move eastwards. In strong El Niños deeper thermocline off S. America means upwelled water is warm and nutrient poor.

ENSO/El Niño state. Sea surface is warm in central and eastern Pacific. Less cold water is pulled up along west coast of South America. Hot air rises in central Pacific, travels east and west before cooling and descending.

4-4-6-hydbrid forecasting

short-term rainfall Probabilistic forecasts blending with radar nowcasts and MM5

Short-term Quantitative Precipitation Forecasts (QPFs) can be achieved from numerical weather prediction (NWP) models or radar nowcasting, that is the extrapolation of the precipitation at a future time from consecutive radar scans. Hybrid forecasts obtained by merging rainfall forecasts from radar nowcasting and NWP models are potentially more skilful than either radar nowcasts or NWP rainfall forecasts alone.

The paper provides an assessment of deterministic and probabilistic high-resolution QPFs achieved by implementing the Short-term Ensemble Prediction System developed by the UK Met Office. Both radar nowcasts and hybrid forecasts have been performed. The results show that the performance of both deterministic nowcasts and deterministic hybrid forecasts decreases with increasing rainfall intensity and spatial resolution. The results also show that the blending with the NWP forecasts improves the performance of the forecasting system. Probabilistic hybrid forecasts have been obtained through the modelling of a stochastic noise component to produce a number of equally likely ensemble members, and the comparative assessment of deterministic and probabilistic hybrid forecasts shows that the probabilistic forecasting system is characterised by a higher discrimination accuracy than the deterministic one. Copyright © 2011 John Wiley & Sons, Ltd [7].

4-5-Weather alerts and advisories

The world's first televised weather forecasts, including the use of weather maps, were experimentally broadcast by the BBC in 1936. This was brought into practice in 1949 after World War II. In the late 1970s and early 80s, John Coleman, the first weatherman on ABC-TV's Good Morning America, pioneered the use of on-screen weather satellite information and computer graphics for television forecasts. Some weather channels have started broadcasting on live broadcasting programs such as YouTube and Periscope to reach more viewers. A major part of modern weather forecasting is the severe weather alerts and advisories that the national weather services issue in the case that severe or hazardous weather is expected. This is done to protect life and property. Some of the most commonly known of severe weather advisories are the severe thunderstorm and tornado warning, as well as the severe thunderstorm and tornado watch. Other forms of these advisories include winter weather, high wind, flood, tropical cyclone, and fog. Severe weather advisories and alerts are broadcast through the media, including radio, using emergency systems as the Emergency Alert System, which break into regular programming. There are a number of sectors with their own specific needs for weather forecasts and specialist services are provided to these users:

- Air traffic
- Marine
- Agriculture
- Forestry
- Utility companies
- Other commercial companies
- Military applications

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Chapter 5 Uncertainty Analysis in FFS

"Flood Forecasting Systems (FFS), include atmospheric, surface water and subsurface water (unsaturated and groundwater sub system) systems. So in this chapter after describing methods of uncertainty analysis, developed the concepts to apply these methods in these systems based on meteorologic (as a physical process) and hydrologic (as a lumped and hydraulical process) forecasting models that is the same FFS.

*Computer modeling for the next generation of hydrological modelers is inevitable (**Mchine Learning**).* Daliri.F 2020

5-1 Uncertainty analysis methods

In this section, discuss available methods and tools to quantifying uncertainties in performance assessment (PA) models. Main sources of uncertainty are [1], [3]:

- Physical variability
- Data uncertainties
- Model error

The uncertainty quantification methods are described here are four types include:

(1) quantification of uncertainty in the inputs to the PA models,
(2) propagation of input uncertainty through the PA models,
(3) model error quantified through verification and validation activities, and
(4) probabilistic PA.
Random variable and random process descriptions of physical variability are outlined. Methods for handling data uncertainty through flexible families of probability distributions, confi-dence bounds, interval analysis and Bayesian analysis are described. Useful surrogate modeling and sensitivity analysis techniques for efficient uncertainty propagation analysis are discussed, as well as methods to quantify the various sources of model error. Statistical hypothesis testing techniques (both classical and Bayesian) are discussed for the validation of PA models, and a Bayesian approach to quantify the confidence in model prediction with respect to field conditions is developed. First-order approximations as well as efficient Monte Carlo sampling techniques for probabilistic PA are described [1] , [3].

Uncertainty quantification is important in assessing and predicting performance of complex engineering systems, especially in the absence of adequate experimental or real-world data. Simulation of complex physical systems involves multiple levels of modeling ranging from the material to component to subsystem to system. Interacting models and simulation codes from multiple disciplines (multiple physics) may be required, with iterative analyses between some of the codes. As the models are integrated across multiple disciplines and levels, the problem becomes more complex and assessing the predictive capability of the overall system model becomes more difficult. Many factors contribute to the uncertainty in the prediction of the system model including: variability in model input variables, modeling errors, assumptions and approximations, measurement errors, and sparse and imprecise data.

Figure 5-1 shows the four stages, within a conceptual framework for systematic quantification, propagation and management of various types of uncertainty. The methods discussed in this book address all the four steps shown in Figure 5-1. While uncertainty has been dealt with using probabilistic as well as non probabilistic (e.g., fuzzy sets, possibility theory, evidence theory) formats in the literature, this report will focus only on probabilistic analysis, mainly because the mathematics of probabilistic computation are very well established, whereas the non-probabilistic methods are still under development and generally result in interval computations that are expensive when applied to large problems with many variables.

The different stages of analysis in Figure 5-1 are not strictly sequential. For example, stage 3 (verification and validation –V&V) appears after system analysis and uncertainty propagation. However, it is almost impossible to perform V&V on the system scale, because of extrapolation in time and space; therefore V&V is usually done for the sub-models. Also, several of the inputs to the overall system model may be calibrated based on the results of sub-model analysis, sensitivity analysis, and V&V activities. Thus the four stages in Figure 5-1 simply group together the different types of analysis, and might occur in different sequences for different problems and different sub-models.

The quantification of uncertainty in current PAs is limited to quantifying the probability distributions of key parameters. A more comprehensive implementation of uncertainty quantifycation for environmental PAs has been hampered by the numerous sources of uncertainty and the long time durations considered in the PAs. The methods presented here provide a basis for advancing the current state of the art in uncertainty quantification of environmental PAs.

The remainder of this section is organized as follows: Section 5-1-1 discusses methods to quantify the uncertainty in the inputs to the system analysis model, addressing both physical variability and data uncertainty. Model error is addressed in Sections 5-1-2 and 5-1-3 and in section 5-1-4 discuss probabilistic PA.

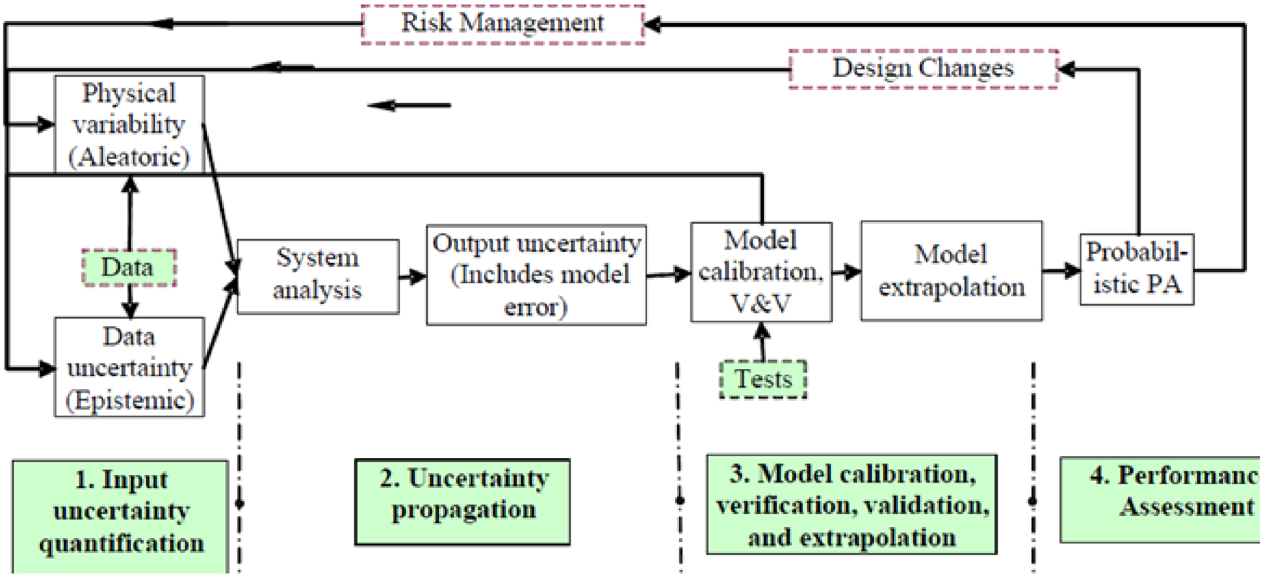

Figure 5-1. Uncertainty Quantification, Propagation and Management Framework [1]

[1] The box Data in the input uncertainty quantification stage includes laboratory data, historical field data, literature sources, and expert opinion.
[2] The box Design Changes may refer to conceptual, preliminary, or detailed design, depending on the development stage.
[3] The boxes Design Changes and Risk Management are outside the scope of this book, although they are part of the overall uncertainty framework.

5-1-1- Input uncertainty quantification

Physical variability of parameters can be quantified through random variables by statistical analysis. Parameters that vary in time or space are modeled as random processes or random fields with appropriate correlation structure. Data uncertainty that leads to uncertainty in the distribution parameters and distribution types can be addressed using confidence intervals and Bayesian statistics. Methods to include several sources of data uncertainty, namely, sparse data, interval data and measurement error, are discussed.

5-1-1-1- Physical variability

This type of uncertainty, also referred to as aleatory or irreducible uncertainty, arises from natural or inherent random variability of physical processes and variables, due to many factors such as environmental and operational variations, construction processes, and quality control. This type of uncertainty is present both in system properties (e.g., material strength, porosity, diffusivity, geometry variations, reaction rates) and external influences and demands on the system (e.g., concentration of chemicals, temperature, humidity, mechanical loads). As a result, in model-based prediction of system behavior, there is uncertainty regarding the precise values for model parameters and model inputs, leading to uncertainty about the precise values of the model output. Such quantities are represented in engineering analysis as random variables, with statistical parameters such as mean values, standard deviations, and distribution types estimated from observed data or in some cases assumed. Variations over space or time are modeled as random processes.

Examples of Cementitious Barrier Model input variables with physical variability (i.e., inherent, natural variability) include:

• Material properties (mechanical, thermal, porosity, permeability, diffusivity, roughness coefficient,..)
• Geometrical properties (structural dimensions, concrete cover depth,..)
• External conditions (mechanical loading, boundary conditions, physical processes such as freeze-thaw, chemical processes such as carbonation, chloride or sulfate attack).

Many uncertainty quantification studies have only focused on quantifying and propagating the inherent variability in the input parameters. Well-established statistical (both classical and Bayesian) methods are available for this purpose.

5-1-1-1-1 Modeling variability in system properties

In probabilistic analysis, the sample–to–sample variations (random variables) in the parameters are addressed by defining them as random variables with probability density functions (PDFs). This assumes that the system/material is homogeneous on a macroscale. For example, chloride ion diffusivity has been modeled using a lognormal distribution (Hong, 2000; Gulikers, 2006; Rafiq et al., 2004; Chen, 2006) and water–cement ratio has been modeled using a normal distribution (Chen, 2006) and uniform and triangular distributions (Kong et al., 2002).
Some parameters may vary not only from sample to sample (as is the case for random variables), but also in spatial or time domain. Parameter variation over time and space can be modeled as random processes or random fields. For example, concrete cover depth and compressive strength have been modeled as random fields using squared exponential correlation functions (Stewart and Mullard, 2007).
Some well known methods for simulating random processes are spectral representation (SR)

(Gurley, 1997), Karhunen-Loeve expansion (KLE) (Ghanem and Spanos, 2003, Huang et al., 2007; Mathelin et al., 2005), and polynomial chaos expansion (PCE) (Huang et al., 2007; Mathelin et al., 2005; Red-Horse and Benjamin, 2004). The PCE method has been used to represent the stochastic model output as a function of stochastic inputs. Consider an example of representing a random process using KLE, expressed as

5-1 $$\varpi(x,\chi)=\varpi(x)+\sum_{i=1}^{\infty}\sqrt{\lambda_i}\,\xi_i(\chi)f_i(x)$$

where:
$\varpi(x)$ is the mean of the random process $\varpi(x, \chi)$,λi and $f_i(x)$ are eigenvalues and eigenfunctions of $C(x1,x2)$, and $\xi i(\chi)$ is a set of uncorrelated standard normal random variables (x is a space or time coordinate, and χ is an index representing different realizations of the random process).
Using Equation (5-1), realizations of the random process $\varpi(x, \chi)$ can be easily simulated by generating samples of the random variables $\xi(\chi)$, and these realizations of $\varpi(x,\chi)$ can be used as inputs to PA.

5-1-1-1-2 Modeling variability in external conditions
Some boundary conditions (e.g., temperature and moisture content) might exhibit a recurring pattern over shorter periods and also a trend over longer periods. An example of variability in an external condition, i.e., rainfall, is illustrated in Figure 5-2. It is evident from the figure that the rainfall data has a pattern over a period of 1 year and a downward trend over a number of years. These can be numerically represented by a seasonal model using an autoregressive integrated moving average (ARIMA) method generally used for linear (The current observation can be expressed as a linear function of past observations) nonstationary (A process is said to be non-stationary if its probability structure varies with the time or space coordinate) processes (Box et al., 1994). This method can be used to predict the temperature or the rainfall magnitudes in the future so that it can be used in the durability analysis of the structures under future environmental conditions.

5-1-1-1-3 Stationary external processes
For a stationary process (A process is said to be stationary if its probability structure does not vary with the time or space coordinate), the ARIMA method expresses the observation at the t_th time step in terms of the observations at previous time steps as:

5-2 $$z_t=c+\sum_{i=1}^{p}\phi_i z_{t-i}+\varepsilon_t$$

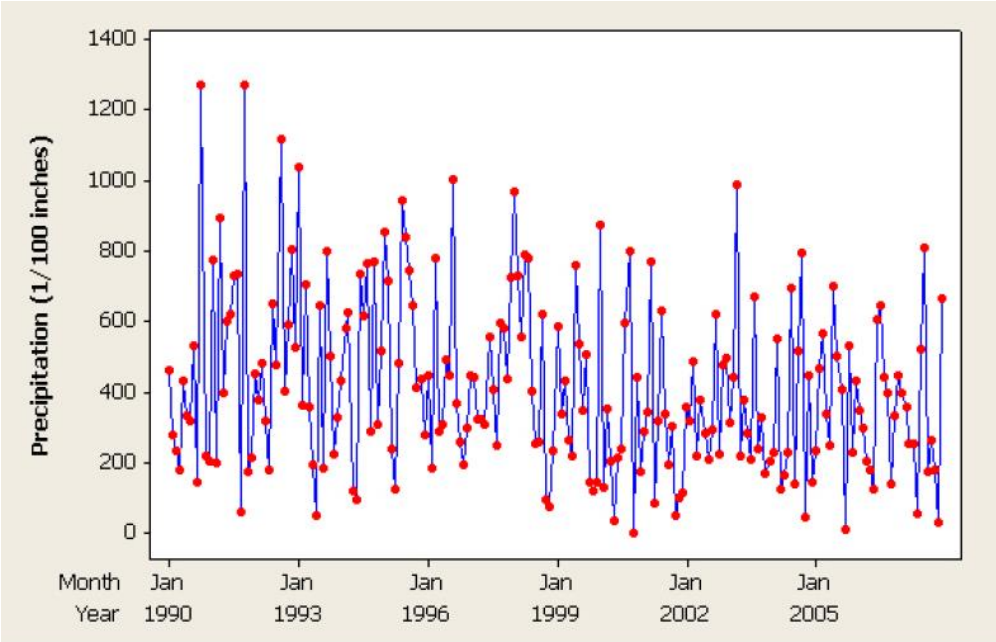

Figure 5-2 Precipitation Data for Aiken, SC (National Oceanic and Atmospheric Administration)[1]

where:

z_t and z_{t-i} are observations at the t^{th} and $(t-i)^{th}$ time steps, c is a constant, ϕ_is are coefficients and ε_t is the error between the observed and the predicted values at t^{th} time step.

Assuming that the error at *t_th* time step is also dependent on the errors at previous time steps, ε_t can also be expressed as:

5-3
$$\varepsilon_t = c_1 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

c1 is a constant and θi are coefficients.

Using a backward operator B such that $B^i z_t = z_{t-i}$ and combining Eqs. (5-2) and (5-3), results in Equation 5-4.

5-4
$$\phi_p(B) z_t = \theta_q(B) \varepsilon_t$$

where:

ϕ_p(B) and θ_q(B) are polynomials of pth and qth order. The coefficients of the polynomials can be determined using the least-squares method.

5-1-1-1-4 Non-Stationary external processes

A random non-stationary process fluctuates about a mean value that exhibits a specific pattern. If the differences in levels of fluctuation are considered, the process can be simulated using the same method as for stationary processes. For example, differentiating a second order polynomial twice will result in a constant. Thus, a non-stationary process of dth degree can be expressed as:

5-5
$$\phi_p(B) \nabla^d z_t = \theta_q(B) \varepsilon_t$$

∇ is called the backward difference operator of the d_th degree. If the process exhibits patterns over a shorter period (s) and a trend over a longer period, the process can be expressed as:

5-6 $$\Phi_P(B^s)\nabla_s^D z_t = \Theta_Q(B^s)\varepsilon_t$$

where:

$\Phi_p(B^s)$ and $\Phi_Q(B^s)$ are polynomials of order P and Q, $B^s z_t = z_{t-s}$, and D is the order of differentiation.

A similar model may be used to relate the current error (error between observation and model prediction at t_th time step) to the previous errors (errors between observations and model predictions at previous time steps) as:

5-7 $$\varphi_p(B)\nabla^d \varepsilon_t = \theta_q(B)a_t$$

where: φp(B) and θq(B) and are polynomials of order p and q, d is the order of differentiation and t a is a white noise process. The fi nal model is obtained by combining Eqs. (5-6- and (5-7) as:

5-8 $$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D z_t = \theta_q(B)\Theta_Q(B^s)a_t$$

Eq. (5-9) is referred to as a general multiplicative model of order (p*d*q) * $(P*D*Q)_s$. This method can be used to simulate a seasonal process.

It may also be important to quantify the statistical correlations between some of the input random variables. Many previous studies on uncertainty quantification simply assume either zero or full correlation, in the absence of adequate data. A Bayesian approach maybe pursued for this purpose, as described in next subsection.

5-1-1-2- Data uncertainty

This type of uncertainty falls under the category of epistemic uncertainty (i.e.,knowledge or information uncertainty) or reducible uncertainty (i.e., the uncertainty is reduced as more information is obtained). Data uncertainty occurs in different forms. In the case of a quantity treated as a random variable, the accuracy of the statistical distribution parameters depends on the amount of data available. If the data is **sparse**, the distribution parameters themselves are uncertain and may need to be treated as **random variables**. On the other hand, information may be **imprecise** or qualitative, and it is not easy to treat this type of uncertainty through random variables. In some cases, data regarding some variables may only be available as a range of values, based on expert opinion. Non-probabilistic representations such as **fuzzy sets** and **evidence theory** are available for describing such uncertainties. **Measurement error** (either in the laboratory or in the field) is another important source of data uncertainty.

A Bayesian updating approach is described below to quantify uncertainty due to **inadequate** statistical data and **measurement** errors (ε_{exp}). This is consistent with the framework proposed in Figure 5-1, and is used to update the statistics of different physical variables and their distribution parameters. The prior distributions are based on available data and expert judgment, and these are updated as more data becomes available through experiments, analysis, or real-world experience.

5-1-1-2-1 Sparse statistical data

For any random variable that is quantitatively described by a probability density function, there is always uncertainty in the corresponding distribution **parameters** due to small sample size. As testing and data collection activities are performed, the state of knowledge regarding the uncertainty changes, and a **Bayesian** updating approach can be implemented. For example, suppose we decide that an input variable X follows a Gaussian distribution $N(\mu,\sigma^2)$ with μ and σ estimated from the data.

There is uncertainty in the normal distribution **assumption**, as well as in the estimates of the distribution parameters μ and σ, depending on the sample size. In the Bayesian approach, μ (mean) and σ (standard deviation) are also treated as random variables, and their statistics are updated based on new data. However, we do not know the distribution of μ and σ a priori, so we may assume Gaussian for μ and Gamma distribution for $\phi = \sigma^{-2}$ as an initial guess for example, and then do a Bayesian update after more data is collected.

The Bayesian approach also applies to **joint distributions** of multiple random variables, which also helps to include the uncertainty in correlations between the variables. A prior joint distribution is assumed (or individual distributions and correlations are assumed), and then updated as data becomes available.

Instead of assuming a well known prior distribution form (e.g., uniform, normal) for sparse data sets, either **empirical distribution** functions, or **flexible families** of distributions based on the data can be constructed.

A **bootstrapping technique** (Bootstrapping is a data-based simulation method for statistical inference by re-sampling from an existing data set (Efron et al., 1994)) can then be used to quantify the uncertainty in the distribution parameters. The empirical distribution function is constructed by ranking the observations from lowest to highest value, and assigning a probability value to each observation.
Examples of flexible distribution families include the: Johnson family, Pearson family, gamma distribution, and stretched exponential distribution. The use of the Johnson family distribution has been explored by Marhadi et al., 2008, and extended to quantify the uncertainty in distribution parameters by McDonald et al., 2009. In constructing the Johnson family distribution, the available data is used to calculate the first four moments, and then the distribution form is chosen based on the values of the four moments. A jack-knife procedure is used to estimate the uncertainty in the distribution parameters, based on repeated estimation by leaving out one or more data points in each estimation.

5-1-1-2-2 Measurement error
The measured quantity y_{exp} usually deviates from the unknown true value y_{true} due to the uncertainties in the **test setup**, **equipment**, **environment**, and **operator**. For example, large errors in the measurement of expansion due to **sulfate attack** can be seen in the experiments performed by Ferraris et al., 1997.
The measurement error ε_{exp} can be expressed as $y_{exp} = y_{true} + \varepsilon_{exp}$. The measurement error in each input variable in many studies (e.g., Barford, 1985) is assumed to be independent and identically distributed (IID) with zero mean and an assumed variance,($\varepsilon_{exp} \sim N(0,\sigma^2_{exp})$.
Due to the measurement uncertainty, the distribution parameter σ_{exp} cannot be obtained as a deterministic value. Instead, it is a random variable with a prior density $\Tau(\sigma_{exp})$. Thus, when new data is available after testing, the distribution of σ_{exp} can be easily updated using the Bayes theorem.
Another way to represent measurement error ε_{exp} is through an **interval** only, and not as a random variable. In that case, one can only say the true value y_{true} lies in the interval [y_{exp} – ε_{exp}, y_{exp} + ε_{exp}] without any probability distribution assigned to ε_{exp}. Methods to include data in interval format are discussed next.

5-1-1-2-3 Data available in interval format
Some quantities in the system model may not have probabilistic representation, since data may be **sparse** or may be based on **expert** opinion. Some experts might only provide information about a range of possible values for some model input variable. Representations such as **fuzzy sets**, **possibility theory**, and **evidence theory** have been used. This section is focused on probabilistic methods to include interval data.
Transformations have been proposed from a nonprobabilistic to probabilistic format, through the maximum likelihood approach (Langley, 2000; Ross et al., 2002).

Such transformations have attracted the criticism that information is either added or lost in the process.

Two ways to address the criticism are:

(1) construct empirical distribution functions based on interval data collected from multiple experts or experiments(Ferson et al., 2007); or

(2) construct flexible families of distributions with bounds on distribution parameters based on the interval data, without forcing a distribution assumption (McDonald et al., 2008).

These can then be treated as random variables with probability distribution functions and combined with other random variables in a Bayesian framework to quantify the overall system model uncertainty. The use of families of distributions will result in multiple probability distributions for the output, representing the contributions of **both physical variability and data uncertainty.**

5-1-2- Uuncertainty propagation analysis

Both classical and Bayesian probabilistic approaches can be investigated to propagate uncertainty between individual sub-models and through the overall system model. To reduce the computational expense, surrogate models can be constructed using several different techniques. Methods for sensitivity analysis in the presence of uncertainty are discussed.

In this section, methods to quantify the contributions of different sources of uncertainty and error as they propagate through the system analysis model, including the contribution of model error, are discussed, in order to quantify the overall uncertainty in the system model output.

This section will cover two issues:

(1) quantification of model output uncertainty, given input uncertainty (both physical variability and data uncertainty), and

(2) quantification of model error (due to both model form selection and solution approximations).

Several uncertainty analysis studies, including a study with respect to the Yucca Mountain high-level waste repository, have recognized the distinction between physical variability and data uncertainty (Helton and Sallaberry, 2009) [1]. As a result, these methods evaluate the variability in an inner loop calculation and data uncertainty in an outer loop calculation. Another example is provided by Holdren et al., 2006 in a baseline risk assessment study with respect to the Idaho Cleanup Project, where contributions of different sources of uncertainty are separately analyzed, such as from inventory, infiltration, sorption characteristics, model calibration, and simulation periods.

5-1-2-1- Propagation of Physical Variability

Various probabilistic methods (e.g., **Monte Carlo simulation and first-order or second-order analytical approximations**[3]) have been studied for the propagation of physical variability in ~~model inputs and model parameters, expressed through random variables and random process~~

or fields. **Stochastic finite element** methods (e.g., Ghanem and Spanos, 2003; Haldar and Mahadevan, 2000) have been developed for single discipline problems in structural, thermal, and fluid mechanics. An example of such propagation is shown in Figure 5-3.

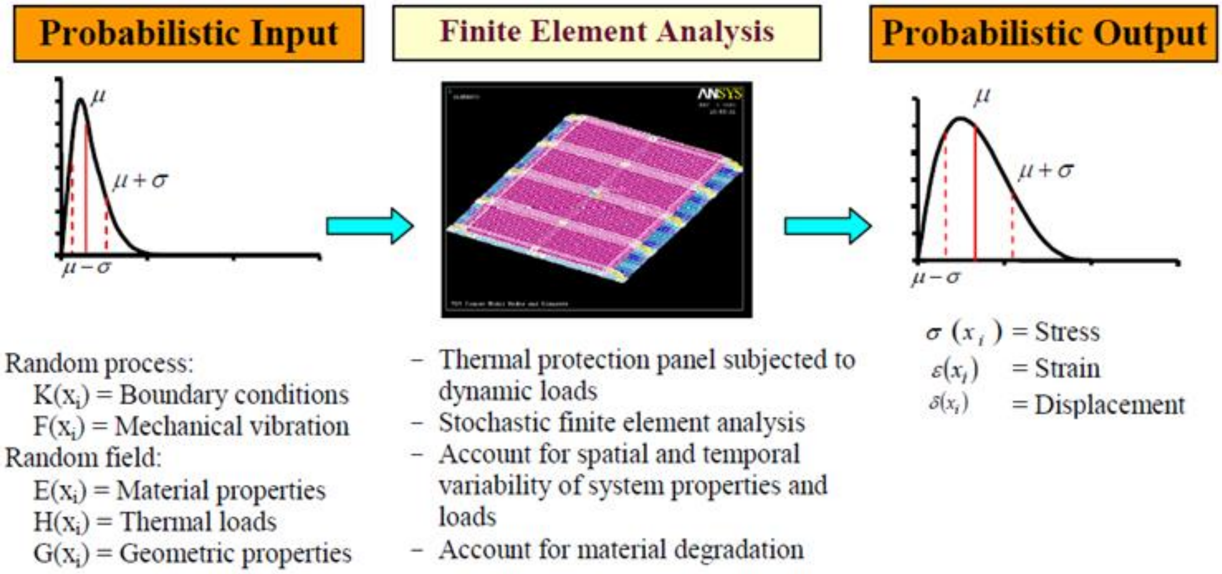

Figure 5-3 Example of Physical Variability Propagation [1]

Several types of combinations of **system analysis** model and **statistical analysis** techniques are available:
• Monte Carlo simulation with the deterministic system analysis as a black-box (e.g., Robert and Cesalla, 2004) to estimate model output statistics or probability of regulatory compliance;
• Monte Carlo simulation with a surrogate model to replace the deterministic system analysis model (e.g., Ghanem and Spanos, 2003; Isukapalli et al.,1998; Xiu and Karniadakis, 2003; Huang et al., 2007), to estimate model output statistics or probability of regulatory compliance;
• Local sensitivity analysis using finite difference, perturbation or adjoint analyses, leading to estimates of the first-order or second-order moments of the output (e.g., Blischke and Murthy, 2000); and
• Global sensitivity and **effects** analysis, and analysis of variance in the output (Box et al., 1978).
These techniques are generic, and can be applied to multi-physics analysis with multiple component modules as in the **PA of cementitious barriers**. However, most applications of these techniques have only considered physical variability. The techniques need to include the contribution of data uncertainty and model error to the overall model prediction uncertainty.

Computational effort is a significant issue in practical applications, since these techniques involve a number of repeated runs of the system analysis model. The system analysis may be replaced with an **inexpensive surrogate model** in order to achieve computational efficiency; this is discussed in Section 5-1-2-3. Efficient Monte Carlo techniques have also been pursued to reduce the number of system model runs, including Latin hypercube sampling (**LHS**) (Mckay et al., 1979; Farrar et al., 2003) and importance sampling (Mahadevan and Raghothamachar, 2000; Zou et al. 2003).

5-1-2-2- Propagation of Data Uncertainty

Three types of data uncertainty were discussed in prior Section. Sparse point data results in uncertainty about the parameters of the probability distributions describing quantities with physical variability. In that case, uncertainty propagation analysis takes a nested implementation. In the outer loop, samples of the distribution parameters are randomly generated, and for each set of sampled distribution parameter values, probabilistic propagation analysis is carried out as in Section 5-1-2-1. This results in the computation of multiple probability distributions of the output, or confidence intervals for the estimates of probability of non-compliance in PA.

In the case of measurement error, choice of the uncertainty propagation technique depends on how the measurement error is represented. If the measurement error is represented as a **random** variable, it is simply added to the measured quantity, which is also a random variable due to physical variability. Thus a sum of two random variables may be used to include both physical variability and measurement error in a quantity of interest. If the measurement error is represented as an **interval**, one way to implement probabilistic analysis is to represent the interval through families of distributions or upper and lower bounds on probability distributions, as discussed in Section 5-1-1-2-3. In that case, **multiple** probabilistic analyses, using the same **nested** approach as in the case of sparse data, can be employed to generate multiple output distributions or confidence intervals for the model output. The same approach is possible for interval variables that are only available as a range of values, as in the case of expert opinion.

Propagation of uncertainty is conceptually very simple, but computationally quite expensive to implement, especially when both physical variability and data uncertainty are to be considered. The presence of both types of uncertainty requires a nested implementation of uncertainty propagation analysis (simulation of data uncertainty in the outer loop and simulation of physical variability in the inner loop). If the system model runs are time-consuming, then uncertainty propagation analysis could be prohibitively expensive. One way to overcome the computational hurdle is to use an inexpensive surrogate model to replace the detailed system model, as discussed next.

5-1-2-3- Surrogate Models

Surrogate models (also known as response surface models) are frequently used to replace the expensive system model, and used for multiple simulations to **quantify the uncertainty** in the output. Many types of surrogate modeling methods are available, such as linear and nonlinear regression, polynomial chaos expansion, Gaussian process modeling (e.g., Kriging model), splines, moving least squares, support vector regression, relevance vector regression, neural nets, or even simple look-up tables. For example, Goktepe et al., 2006 used neural network and polynomial regression models to simulate expansion of concrete specimens under sulfate attack. All surrogate models require training or fitting data, collected by running the full-scale system model repeatedly for different sets of input variable values. Selecting the sets of input values is referred to as statistical design of experiments, and there is extensive literature on this subject. Two types of surrogate modeling methods are discussed below that might achieve computational efficiency while maintaining high accuracy in output-uncertainty quantification. The first method expresses the model output in terms of a series expansion of special polynomials such as Hermite polynomials, and is referred to as a stochastic response surface method (**SRSM**). The second method expresses the model output througha Gaussian process, and is referred to as **Gaussian** process modeling (Kriging method).

5-1-2-3-1 Stochastic Response Surface Method

The common approach for building a surrogate or response surface model is to use least squares fitting based on polynomials or other mathematical forms based on physical considerations. In SRSM, the response surface is constructed by approximating both the input and output random variables and fields through series expansions of standard random variables (e.g. Isukapalli et al., 1998; Xiu and Karniadakis, 2003; Huang et al., 2007). This approach has been shown to be efficient, stable, and convergent in several structural, thermal, and **fluid flow problems**. A general procedure for SRSM is as follows:

• Representation of random inputs (either random variables or random processes) in terms of Standard Random Variables (SRVs) by K-L expansion, as in Equation (5-1).

• Expression of model outputs in chaos series expansion. Once the inputs are expressed as functions of the selected SRVs, the output quantities can also be represented as functions of the same set of SRVs. If the SRVs are Gaussian, the output can be expressed a Hermite polynomial chaos series expansion in terms of Gaussian variables. If the SRVs are non-Gaussian, the output can be expressed by a general Askey chaos expansion in terms of non-Gaussian variables (Ghanem and Spanos, 2003).

• Estimation of the unknown coefficients in the series expansion. The improved probabilistic collocation method (Isukapalli et al., 1998) is used to minimize the residual in the random dimension by requiring the residual at the collocation points equal to zero. The model outputs are computed at a set of collocation points and used to estimate the coefficients.

These collocation points are the roots of the Hermite polynomial of a higher order. This way of selecting collocation points would capture points from regions of high probability (Tatang et al., 1997).

• Calculation of the statistics of the output that has been cast as a response surface in terms of a chaos expansion. The statistics of the response can be estimated with the response surface using either **Monte Carlo simulation** or **analytical approximation**.

5-1-2-3-2 Kriging or Gaussian Process Models

Gaussian process (GP) models have several features that make them attractive for use as surrogate models. The primary feature of interest is the ability of the model to “account for its own uncertainty.” That is, each prediction obtained from a Gaussian process model also has an associated **variance**, or **uncertainty**. This prediction variance primarily depends on the closeness of the prediction location to the training data, but it is also related to the functional form of the response. For example, see Fig. 5-4, which depicts a one-dimensional Gaussian process model. Note how the uncertainty bounds are related to both the closeness to the training points, as well as the shape of the curve.

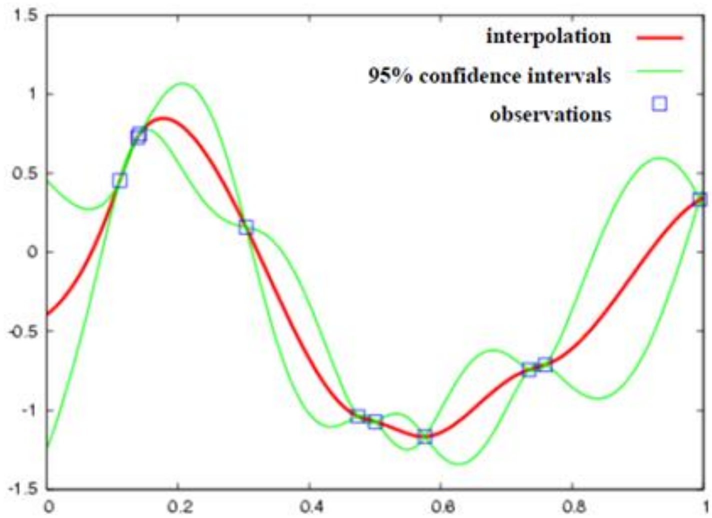

Figure 5-4. Gaussian Process Model With Uncertainty Bounds[1]

The basic idea of the GP model is that the output quantities are modeled as a group of multivariate normal random variables. A parametric covariance function is then constructed as a function of the inputs. The covariance function is based on the idea that when the inputs are close together, the correlation between the outputs will be high. As a result, the uncertainty associated with the model prediction is small for input values that are close to the

training points, and large for input values that are not close to the training points. In addition, the GP model may incorporate a systematic trend function, such as a linear or quadratic regression of the inputs (in the notation of Gaussian process models, this is called the ***mean* function**, while in Kriging it is often called a **trend function**). The effect of the mean function on predictions that interpolate the training data is small, but when the model is used for extrapolation, the predictions will follow the mean function very closely.
Within the GP modeling technique, it is also possible to adaptively select the design of experiments to achieve very high accuracy. The method begins with an initial GP model built from a very small number of samples, and then one intelligently chooses where to generate subsequent samples to ensure the model is accurate in the vicinity of the region of interest. Since the GP model provides the expected value and variance of the output quantity, the next sample may be chosen in the region of highest variance, if the objective is to minimize the prediction variance. The method has been shown to be both accurate and computationally efficient for arbitrarily shaped functions (Bichon et al., 2007).

5-1-2-4- Sensitivity Analysis Methods
Sensitivity analysis serves several important functions:
(1) identification of dominant variables or sub-models, thus helping to focus data collection resources efficiently;
(2) identification of insignificant variables or sub-models of limited significance, helping to reduce the size of the problem and computational effort; and
(3) quantification of the contribution of solution approximation error.
Both local and global sensitivity analysis techniques are available to investigate the quantitative effect of different sources of variation (physical parameters, models, and measured data) on the variation of the model output. The primary benefit of sensitivity analysis to uncertainty analysis is to enable the identification of which physical parameters have the greatest influence on the output (Campolongo et al., 2000; Saltelli et al., 2000). An analysis of the impact of the parametric uncertainty [3] is conducted to weed out those that have an insignificant effect upon the system output. For example, Chen (2006) performed sensitivity analysis to identify the important parameters affecting the **service life** of the **concrete structures.**
Three sensitivity analysis methods are factor screening, local-, and global-sensitivity analysis approaches. Factor screening determines which parameters have the greatest impact on the system output variability, by evaluating the output at the extreme values within the **ranges** of the parameters. For example we can change the cn in SCS method to runoff estimation[4]. Local sensitivity analysis utilizes first-order derivatives of system output quantities with respect to the parameters. It is usually performed for a nominal set of parameter values. For example roughness coefficient n in Manning equation to debit calculations [3]. Global sensitivity analysis typically uses statistical sampling methods, such as Latin Hypercube

Sampling, to determine the total uncertainty in the system output and to apportion that uncertainty among the various parameters. Classical and Bayesian statistical analysis techniques, including the analysis of variance and differential sensitivity analysis, can be pursued to assess the global influence of an input parameter on an output variable by sampling from each input parameter's probability density function or from intervals of possible values.

5-1-2-5- Multi-Physics Models

In the past decade, different approaches have been proposed to quantify the uncertainty for individual physical models or simulation codes (e.g. see, Glimm and Sharp, 1999; Hanson, 1999; Devolder et al., 2002; Bae et al., 2003; Hanson and Hemez, 2003; Oberkampf et al., 2003; Millman et al., 2006; Witteveen and Bijl, 2006). For example, Hanson (1999) proposed a **Bayesian probabilistic** method for quantifying uncertainties in simulation predictions. Bae et al. (2003) used **evidence theory** to handle epistemic uncertainty about a structural system. Mathelin et al. (2004) and Witteveen and Bijl (2006) applied a **polynomial chaos-based stochastic** method for uncertainty propagation in numerical simulations. However, these existing approaches have not accounted for the uncertainty quantification in multiple modules of the system model, where the challenge is to combine data (available from different sources, in different formats) and model predictions regarding different physical phenomena (e.g., diffusion, chemical reaction, and mechanical damage), thus using all available information to quantify the overall prediction uncertainty. Urbina and Mahadevan (2009) have recently proposed a **Bayes network approach** to uncertainty quantification in multi-physics models.

5-1-2-6- Model Error Quantification

Model error: This results from approximate mathematical models of the system behavior and from numerical approximations during the computational process, resulting in two types of error in general – solution approximation error, and model form error. The performance assessment (**PA**) of a complex system involves the use of numerous analysis models, each with its own assumptions and approximations. The errors from the various analysis components combine in a complicated manner to produce the **overall model error**. This is also referred to as **model bias**.

The roles of several types of uncertainty in the use of model-based simulation for performance assessment can be easily illustrated with the following example. Consider the probability of an undesirable event denoted by g(X) < k, which can be computed from:

$$P(g(\mathbf{X}) < k) = \int_{g(\mathbf{X})<k} f_{\mathbf{X}}(\mathbf{x})\ d\mathbf{x} \quad (5\text{-}9)$$

where:
X is the vector of input random variables, $f_X(x)$ is the joint probability density function of X, g(X) is the model output, and k is the regulatory requirement in performance assessment.
Every term on the right hand side of Equation (5-9) has uncertainty. There is **inherent variability** represented by the vector of random variables X, **data uncertainty** (due to inadequate data,…) regarding the distribution type and distribution parameters of $f_X(x)$, and **model errors** in the computation of g(X). Thus it is necessary to systematically identify the various sources of uncertainty and develop the framework for including them in the overall PA uncertainty quantification.
Model errors may relate to governing **equations**, **boundary and initial condition** assumptions, **loading description** or **conceptual model**, and **approximations or errors in solution algorithms** (e.g., truncation of higher order terms, finite element discretization, curve-fitting models for material damage such as S-N curve and …). **Overall model error** may be quantified by **comparing** model prediction and experimental observation, properly accounting for uncertainties in both. This overall error measure combines both model form and solution approximation errors, and so it needs to be considered in two parts. **Numerical errors** in the model prediction can be quantified first, using sensitivity analysis, uncertainty propagation analysis, discretization error quantification, and truncation (residual) error quantification. The **measurement error** in the input variables can be propagated to the prediction of the output. The error in the prediction of the output due to the measurement error in the input variables is approximated by using a **first-order sensitivity analysis** (Rebba et al., 2006). Then the **model form error** can be quantified of **comparing** sum of the all the above errors with overall error, or based on all the above errors, following the approach illustrated for a heat transfer problem by Rebba et al. (2006) [1].

5-1-2-6-1 Solution Approximation Error

Several components of prediction error, such as **discretization error** (denoted by ε_d) and uncertainty propagation analysis error (ε_s) can be considered. Several methods to quantify the discretization error **in finite element analysis** are available in the literature. However, most of these methods do not quantify the actual error; instead, they only quantify some indicator measures to facilitate adaptive mesh refinement. The **Richardson extrapolation** (RE) method comes closest to quantifying the actual discretization error (Richards, 1997). (In some applications, the model is run with different levels of resolution, until an acceptable level of accuracy is achieved; formal error quantification may not be required.) Errors in uncertainty propagation analysis (ε_s) are method-dependent, i.e. **sampling error** occurs in Monte Carlo methods, and **truncation error** occurs in response surface methods (either conventional or polynomial chaos-based). For example, sampling error could be assumed to be a Gaussian random variable with zero mean and variance given by σ^2/N where N, is the number of Monte

Carlo runs, and σ^2 is the original variance of the model output (Rubinstein, 1981). The truncation error is simply the **residual error** in the response surface. Rebba et al. (2006) used the above concept to construct a surrogate model for finite element discretization error in structural analysis, using the stochastic response surface method. Gaussian process models may also be employed for this purpose. Both options are helpful in quantifying the solution approximation error.

5-1-2-6-2 Model Form Error

The overall prediction error is a combination of errors resulting from numerical solution approximations and model form selection. A simple way is to express the total observed error (difference between prediction and observation) as the sum of the following error sources:

$$\varepsilon_{obs} = \varepsilon_{num} + \varepsilon_{model} - \varepsilon_{exp} \quad (5\text{-}10)$$

where:

ε_{num}, ε_{model}, and ε_{exp} represent numerical solution error, model form error, and output measurement error, respectively.

However solution approximation error results from multiple sources and is probably a nonlinear combination of various errors such as discretization error, round-off and truncation errors, and stochastic analysis errors. One option is to construct a regression model consisting of the individual error components (Rebba et al., 2006). The residual of such a regression analysis will include the model form error (after subtracting the experimental error effects). By denoting ε_{obs} as the difference between the data and prediction, i.e., $\varepsilon obs = yexp - ypred$, we can construct the following relation by considering a few sources of numerical solution error (Rebba et al., 2006):

$$\varepsilon_{obs} = f(\varepsilon_h, \varepsilon_d, \varepsilon_s) + \varepsilon_{model} - \varepsilon_{exp} \quad (5\text{-}11)$$

where:

εh, εd, and εs represent output error due to input parameter measurement error, finite element discretization error, and uncertainty propagation analysis error, respectively, all of which contribute to numerical solution error. Rebba et al. (2006) illustrated the estimation of model form error using the above concept for a one dimensional heat conduction problem, assuming a linear form of Eq. (5-11). However, the function $f(\varepsilon h, \varepsilon d, \varepsilon s)$ is nonlinear, and may be approximated through a response surface with respect to the three error variables, using a **polynomial chaos expansion**. The quantity $\varepsilon model - \varepsilon exp$ is simply the residual error of such a response surface. Thus the distribution of model error $\varepsilon model$ is quantified by knowing the distributions of residual error and measurement error. Note that the above approach to quantifying model form error is only within the context of model validation—where actual data is available from targeted validation experiments—and compared with corresponding model predictions. In the context of PA, however, the concern is with extrapolation in time and space, and no direct comparison is possible between prediction and observation (at the time when the PA is done). Quantifying the model errors during extrapolation is difficult, and a

Bayesian methodology might need to be pursued within restrictive assumptions (e.g., no change in physics). The Bayesian approach is discussed in Section 5-1-3.

5-1-3- Model uncertainty quantification (calibration, verification, validation, and extrapolation)

Model calibration is the process of **adjusting model parameters** to obtain good agreement between model **predictions** and **experimental observations** (McFarland, 2008). Both classical and Bayesian statistical methods are discussed for model calibration with available data. One particular concern is how to properly integrate different types of data, available at different levels of the model hierarchy. Assessment of the "**correct**" implementation of the model is called **verification**, and assessment of the degree of agreement of the model response with the available physical observation is called **validation** (McFarland, 2008). Model verification and validation activities help to quantify model error (both model form error and solution approximation error). A possible Bayesian approach is discussed for quantifying the confidence in model extrapolation from laboratory conditions to field conditions.
After quantifying and propagating the physical variability, data uncertainty, and model error for individual components of the overall system model, the probability of meeting performance requirements (and our confidence in the model prediction) needs to be assessed based on extrapolating the model to field conditions (which are uncertain as well), where sometimes very limited or no experimental data is available.
Rigorous verification, validation, and calibration methods are needed to establish credibility in the modeling and simulation. Both **classical and Bayesian statistical** methodologies have been successfully developed during recent years for single physics problems, and have the potential to be extended to multi-physics models of **cementitious barrier systems**. The methods should have the capability to consider multiple output quantities or a single model output at different spatial and temporal points. This section discusses methods for
(1) calibration of model parameters, based on observation data;
(2) validation assessment of the model, based on observation data; and
(3) estimation of confidence in the extrapolation of model prediction from laboratory conditions to field conditions.

5-1-3-1- Model Calibration

Two types of **statistical techniques** may be pursued for model calibration uncertainty, the **least squares approach**, and the **Bayesian approach**. The least squares approach estimates the values of the calibration parameters that minimize the discrepancy between model prediction and experimental observation. This approach can also be used to calibrate surrogate models or low-fidelity models, based on high-fidelity runs, by treating the high-fidelity results similar to experimental data. The second approach is Bayesian calibration (Kennedy and O'Hagan, 2001). This approach is flexible and allows different forms for the calibration factor, and it has been illustrated for a heat transfer example problem (McFarland and Mahadevan, 2007, McFarland, 2008).

In the literature, several researchers have calibrated their models using experimental results, especially if the phenomenon being modeled is complicated and the model is based on simplifying assumptions. For example, Tixier and Mobasher (2003) calibrated two parameters (reaction rate constant and fraction of porosity available for solid product deposition), and Krajcinovic et al. (1992) calibrated one parameter (reaction rate constant), while modeling the degradation of concrete structures under sulfate attack.

5-1-3-2 Model Validation

Model validation involves comparing prediction with observation data (either historical or experimental) when both have uncertainty. Since there is uncertainty in both model prediction and experimental observation, it is necessary to pursue rigorous statistical techniques to perform model validation assessment rather than simple graphical comparisons, provided data is even available for such comparisons. **Statistical hypothesis testing** is one approach to quantitative model validation under uncertainty, and both **classic and Bayesian** statistics have been explored. **Classical hypothesis testing** is a well-developed statistical method for accepting or rejecting a model based on an error statistic (see e.g., Trucano et al., 2001; Hills and Trucano, 2002; Paez and Urbina, 2002; Hills and Leslie, 2003; Rutherford and Dowding, 2003; Dowding et al., 2004; Chen et al., 2004; Oberkampf and Barone, 2006)[1]. Validation metrics have been investigated in recent years based on **Bayesian hypothesis testing** (Zhang and Mahadevan, 2003; Mahadevan and Rebba, 2005; Rebba and Mahadevan, 2006), **reliability-based methods** (Rebba and Mahadevan, 2008), and **risk-based decision analysis** (Jiang and Mahadevan, 2007 & 2008).

In Bayesian hypothesis testing, **prior probabilities** were assigned for the null and alternative hypotheses; P(H0) and P(Ha) respectively, such that P(H0)+ P(Ha) = 1. Here H0 : model error < allowable limit, and Ha: model error > allowable limit. When data D is obtained, the probabilities are updated as P(H0 | D) and P(Ha | D) using the Bayes theorem. Then a Bayes factor (Jeffreys, 1961) B is defined as the ratio of likelihoods of observing D under H0 and Ha; i.e., the first term in the square brackets on the right hand side of:

$$\frac{P(H_0 \mid D)}{P(H_a \mid D)} = \left[\frac{P(D \mid H_0)}{P(D \mid H_a)}\right]\frac{P(H_0)}{P(H_a)} \tag{5-12}$$

If B > 1, the data gives more support to H0 than Ha. Also the confidence in H0, based on the data, comes from the posterior null probability P(H0 | D), which can be rearranged from Eq. (5-12) as:

$$\frac{P(H_0)B}{P(H_0)B + 1 - P(H_0)} \tag{5-13}$$

Typically, in the absence of prior knowledge, **equal probabilities** may be assigned to each hypothesis and thus P(H0) = P(Ha) = 0.5. The posterior null probability can then be further simplifi ed to B/(B+1). Thus a B value of 1.0 represents 50% confi dence in the null hypothesis being true.

The Bayesian hypothesis testing is also able to **account for uncertainty** in the distribution parameters, as mentioned in Section 5-1-1-2. For such problems, the validation metric (**Bayes factor**) itself becomes a random variable. In that case, the probability of the Bayes factor exceeding a specified value can be used as the decision criterion for model **acceptance/rejection**.

Notice that model validation only refers to the situation when controlled, target experiments are performed to evaluate model prediction, and both the model runs and experiments are done under the same set of input and boundary conditions. The validation is done only by comparing the outputs of the model and the experiment. Once the model is calibrated, verified and validated, it may be investigated for confidence in extrapolating to field conditions different from laboratory conditions. This is discussed in the next section.

5-1-3-3 Confidence Assessment in Extrapolation

The **Bayesian** approach can also be used for assessing the confidence in extrapolating model prediction from laboratory conditions to field conditions, from lower resolution to higher resolution analysis, and from the lower level to the higher level in system analysis, through the construction of the **Bayes network** (Jensen and Jensen, 2001). Bayes networks are directed acyclic graphical representations with nodes to represent the random variables and arcs to show the conditional dependencies among the nodes. Data in any one node can be used to update the statistics of all other nodes. This property makes the Bayes network a powerful tool to extrapolate model confidence from laboratory conditions to field conditions (Mahadevan and Rebba, 2005)[1]. After computing the posterior distribution of the output under field conditions, through the Bayes network, the confidence in the prediction can be calculated similar to Section model validation, using the Bayes factor.

Markov Chain Monte Carlo (MCMC) **simulation** is used for numerical implementation of the Bayesian updating analysis. Several efficient sampling techniques are available for MCMC, such as **Gibbs sampling**, the **Metropolis algorithm**, and the **Metropolis-Hastings algorithm** (Gilks et al., 1996). Figure 5-5 shows an illustrative Bayes network for confidence extrapolation. An ellipse represents a random variable and a rectangle represents observed data. A **solid line arrow** represents a **conditional probability** link, and a **dashed line arrow** represents the link of a variable to its observed data if available. The probability densities of the variables Ω, z, and y are updated using the validated data Y. The updated statistics of Ω, z, and y are then used to estimate the updated statistics of the decision variable d (i.e., assessment metric). In addition, both model prediction and predictive experiments are related to input variables X via physical parameters Φ. Note that there is no observed data available for d; yet the confidence in the prediction of d, can be calculated by making use of observed data in several other nodes and propagation of posterior statistics through the Bayes network. The Bayes network thus links the various simulation codes and corresponding experimental observations to facilitate two objectives:

(1) uncertainty quantification and propagation and

(2) extrapolation of confidence assessment from validation domain to application domain.

Bayesian method described in sub sections 5-3.

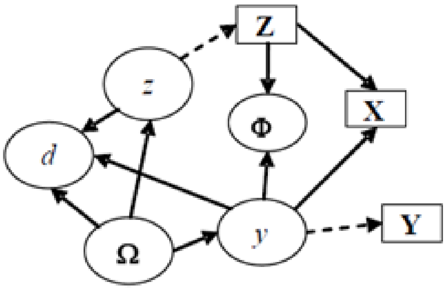

Figure 5-5. Bayes Network [1]

5-1-4- Probabilistic performance assessment

Limit-statebased reliability analysis methods are discussed to help quantify the **PA** results in a probabilistic manner. Methods are also discussed to compute the confidence bounds in probabilistic PA results. **Monte Carlo simulation** with high-fidelity analyses modules is computationally expensive; hence surrogate (or abstracted) models are frequently used with Monte Carlo simulation. In that case, the uncertainty or error introduced by the **surrogate** model also needs to be quantified. Several methods are available in the reliability methods literature to efficiently perform probabilistic performance assessment, as fast alternatives to expensive Monte Carlo simulation. Performance assessment can be conducted with respect to **single** or multiple requirements. Efficient reliability analysis techniques that are based on first-order or second-order approximations or adaptive importance sampling can be used for this purpose. When multiple requirements are defined, computation of the overall probability of satisfying multiple performance criteria requires integration over a multidimensional space defined by unions and intersections of individual events (of satisfaction or violation of individual criteria). An important observation here is that the same methods that are described here for **reliability analysis** can also be used to compute the cumulative distribution function (**CDF**) of the output, which may be of more general interest with respect to uncertainty quantification of model output. The term reliability analysis here refers only to computing the probability of exceeding or not meeting a single **threshold value**, which is a special case of constructing the entire CDF. This section will discuss methods for probabilistic performance assessment with respect to individual criteria and multiple criteria.

5-1-4-1 Individual Criteria

Probabilistic performance assessment can be based on the concept of a limit state that defines the boundary between success and failure for a system (Haldar and Mahadevan, 2000). The limit state function, g, is derived from a system performance criterion and formulated such that g < 0 indicates failure. If the input parameters in the system analysis are uncertain, so will be the predicted value of g. The probability of system failure, i.e. P(g < 0) may be obtained from the volume integral under the **joint probability density function** of the input random variables over the failure domain as

5-14 $$P_f = \int \dots \int_{g \le 0} f_X(x_1, x_2, \dots, x_n)\ dx_1 dx_2 \dots dx_n$$

where:

P_f is the probability of failure, f_x is the joint probability density of a random variable vector X with n elements; vector x represents a single realization of X. Note that the integral is taken over the failure domain, or where g ≤ 0, so P_f = P(g ≤0).

The **basic Monte Carlo simulation method** evaluates the above integral by drawing random samples from the distributions of the variables X, and by evaluating whether g ≤ 0 in each run. Then the failure probability is simply the number of samples with g ≤ 0 divided by the total number of samples. While this technique is very simple to implement, it is also very expensive for problems with low failure probability.

The First Order Reliability Method (**FORM**) approximately estimates the failure probability as $P_f = \Phi(-\beta,)$ where β is the minimum distance from the origin to the limit state in the space of uncorrelated standard normal variables (In general, a set of random variables x may be non-normal and correlated, but these may be transformed to an uncorrelated standard normal space (i.e. the space of random normal variables with 0 mean and unit standard deviation) via a transformationT, i.e $\eta = T(x)$.), as shown in Figure 5-6 (Hasofer and Lind, 1974). The minimum distance point on the limit state is referred to as the most probable point (**MPP**), and β is referred to as the reliability index. Finding the MPP is an optimization problem:

5-15 $$\text{Minimize } \beta = \|\eta\| \text{ , subject to } g_\eta(\boldsymbol{\eta}) = 0$$

where:

η is the vector of random variables in the space of uncorrelated standard normal variables, and ||η|| denotes the norm of that vector.

Several optimization techniques, such as **Newton search** (Rackwitz and Fiessler, 1978), and **sequential quadratic programming** (Schittkowski, 1983) can be used to find the MPP. Second-order reliability methods (**SORM**) are also available for higher accuracy; these take into account the curvature of the limit state in the failure probability calculation (e.g., Breitung, 1984; Tvedt, 1990). Compared to basic Monte Carlo simulation, FORM and SORM require many fewer iterations to converge to the MPP, and thus drastically reduce the computational expense.

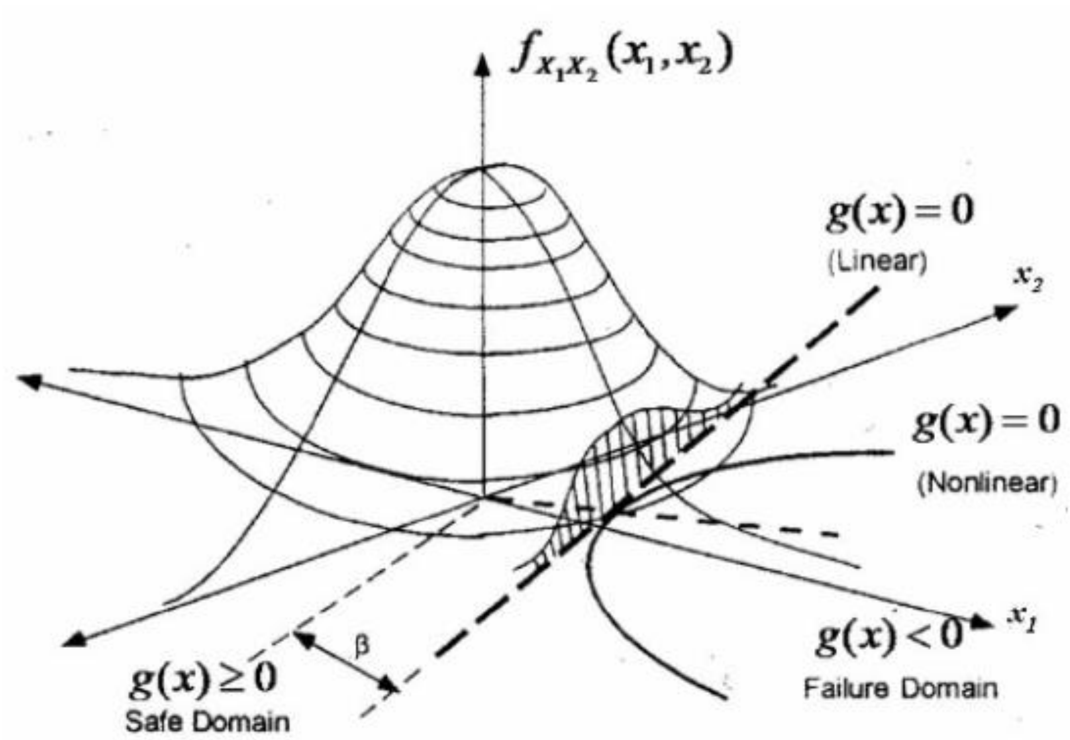

Figure 5- 6. First-order Reliability Method [1]

5-1-4-2 Multiple Criteria

When a PA is conducted with respect to multiple requirements, the overall system-level probability of meeting the requirements is calculated through **unions or intersections of individual failure probabilities**.

In the case of unions (i.e., system fails if any one of the individual criteria is not met), the failure probability is:

5-16 $$P_{F,Series} = P\{\bigcup_k g_k(\mathbf{x}) \leq 0\}$$

This system failure probability may be computed using either Monte Carlo simulation, or by extending the results of the first-order approximation in Section 5-1-4-1. Let B be the vector of reliability indices for each of the limit states, and the elements of the matrix R be the dot products of the corresponding α vectors (unit gradient vector of the limit state at the MPP in standard normal space) obtained from the FORM analysis for each limit state. Then the system failure probability in the above equation can be approximated as 1 – Φ(B, R), where Φ(B, R) is the standard normal multivariate CDF with correlation matrix R.

Closed-form representations of Φ(B, R) exist for the bivariate case (Dunnett and Sobel, 1954). If more than two limit states are considered, then one may elect to use bounding formulae (Ditlevsen, 1979), **importance sampling methods** (e.g., Mahadevan and Dey, 1998; Ambartzumian et al., 1998), **multiple linearizations** (Hohenbichler and Rackwitz, 1987), or a **moment-based approximation** (Pandey, 1998). For nonlinear limit states, the joint failure domain may be identified through an **iterative linearization procedure** (Mahadevan and Shi, 2001).
Similar concepts can be applied when the system failure is defined through intersections of individual failures (i.e., system fails only if all the individual criteria are not met). In that case, the failure probability is:

5-17 $$P_{F,Parallel} = P\{\bigcap_k g_k(\mathbf{x}) \le 0\}$$

Again, the failure probability of the **parallel system** can be calculated either by **Monte Carlo simulation**, or from the results of the **FORM** analysis of its components as Φ (-B, R). In case FORM-based estimation is too approximate, Monte Carlo simulation can be used for higher accuracy, but with a large number of simulations. Efficient sampling techniques such as importance sampling (Mahadevan and Dey, 1998) may be used to reduce the computational expense.
In some cases, **overall system failure** definition may not be a simple union or intersection of individual failures, but may need to be represented as combinations of unions and intersections. In most cases, the system will not necessarily be in one of the two states (failed or safe), but in one of several levels of performance or degradation. Accounting for evolution of system states through time considerably increases the computational effort. The effort increases further when iterative multi-physics analysis is necessary, as in the case of several simultaneously active degradation processes. One option is to use first-order, second moment approximations to B and R (Mahadevan and Smith, 2006), to reduce the computational expense, but at the cost of accuracy. A trade-off between accuracy and computational expense may be necessary.
An important observation to note is that the probability calculations described in this section and prior are only with respect to physical variability, represented by the random variables X. The presence of data uncertainty and model errors makes the probability estimates themselves uncertain. Thus one can construct confidence bounds on the CDF of the output, based on a nested two-loop analysis. In the outer loop, realizations of the variables representing information uncertainty (such as distribution parameters of the probability distributions) and model errors are generated, and for each such realization, the output CDF is constructed in the inner loop. The collection of the resulting multiple CDFs is then used to construct the confidence bounds on the CDF. This nested implementation can become

computationally demanding; in that case, a single loop implementation that simultaneously performs both outer loop and inner loop analyses may be pursued (McDonald et al., 2009).
Uncertainty quantification in performance assessment involves consideration of three sources of uncertainty **inherent variability**, **information uncertainty**, and **model errors**. Hear mentioned available methods to quantify the uncertainty in model-based prediction due to each of these sources, and addressed them in four stages – input characterization based on data; propagation of uncertainties and errors through the system model; model calibration, validation and extrapolation; and performance assessment. Flexible distribution families were discussed to handle **sparse data** and **interval data**. **Autoregressive** models were discussed to handle **time dependence**. Methods to quantify model errors resulting from both model form selection and solution approximation were discussed. Bayesian methods were discussed for model calibration, validation and extrapolation. An important issue is computational expense, when iterative analysis between multiple codes is necessary. Uncertainty quantification multiplies the computational effort of deterministic analysis by an order of magnitude. Therefore the use of surrogate models, and first-order approximations of overall output uncertainty, were described to reduce the computational expense.
Many of the methods described here have been applied to mechanical systems that are small in size, or time-independent, and the uncertainties considered were not very large. None of these simplifications is available in the case of long-term performance assessment of engineered barriers for radioactive waste containment, and real-world data to validate long-term model predictions is not available. Thus the extrapolations are based on laboratory data or limited term observations, and come with large uncertainty. Therefore the benefit of uncertainty quantification is not so much in predicting failure probability or similar measures, but in facilitating engineering decision making, such as comparing different design and analysis options, and allocating resources for **uncertainty reduction** through further data collection and/or model refinement.

5-2- Rainfall forecasting

Ensemble forecasting of weather phenomena is vital to disaster management based on risk and uncertainty. Some phenomena such as fog prediction (traffic disasters, bad air quality in poor visibility weather) is complex because fail in understanding of physics process (stratus subsidence, advection, radiative cooling near the ground) and models. Although fog is still not a direct produced by NWP but is diagnosed by local forecasters based either on statistical methods such as model output statistics (MOS; koziara et al. 1983) and neural network or on indirect model output variables or multimodels mesoscale ensemble prediction system [6]. In continue the texts focus on:

- radar rainfall gauge adjustment
- short-term rainfall forecasts based on ensemble precipitation nowcasts
- Short- to Medium-Range of quantitative precipitation forecast (QPF) with NWP models,
- probabilistic rainfall forecast from WRF model,

5-2-1 Adjusted radar QPE [7]

In fact, floods are the most widespread and harmful weather-related natural disasters. Therefore, high-resolution precipitation estimates and forecasts are of significant interest for use in hydrological applications, especially in relation to hilly terrain.

The standard method of collection for quantifying rainfall on the ground is a rain gauge. However, a gauge is often insucient because of the high spatial and temporal variability of rainfall, especially in rural basins scale and in low-density gauge networks. Thus, radar data is widely used to produce a quantitative precipitation estimation (QPE). Owing to their large coverage, high spatial resolution and temporal frequency, weather radars produce observations that adequately represent precipitation structure and evolution. Nevertheless, these radar measurements have limitations (causes uncertainties) that negatively affect the quality of the radar QPE such as:

- Beam blockage by obstacles, such as buildings, trees, or mountains, which constitute a mask preventing rain detection.
- Overshooting and partial beam filling, due to the increase of the sounded volume and beam altitude at key distances from the radar. This might lead to underestimation of rain intensity.
- Clutter, such as echoes from non-meteorological targets like airplanes, birds, insects, and dust particles, or **WIFI interference** which could result in unrealistic precipitation estimations.
- Attenuation of the radar signal, which is the gradual loss of power that occurs during heavy rain. This effect is more important for radars with short wavelengths (C-band & X-band radars).

Therefore, if a QPE with high precision is required from radar data, it is necessary to develop robust algorithms that deal with these influencing factors, especially clutter and signal attenuation effects. There have been several attempts to combine rain gauges and radar data to enhance the quality of radar rainfall estimates.

Here focused on investigating the impact of gauge adjustment on the rainfall estimate from a Moroccan **C-band weather radar** located in Khouribga City. The radar reflectivity underwent a quality check before deployment to retrieve the rainfall amount. The process consisted of clutter identification and the correction of signal attenuation. Thereafter, the radar reflectivity was converted into rainfall depth over a period of 24 h. An assessment of the accuracy of the radar rainfall estimate over the study area (case study follow) showed an overall underestimation when compared to the rain gauges (bias = -6.4 mm and root mean square error [RMSE] = 8.9 mm). The adjustment model was applied, and a validation of the adjusted rainfall versus the rain gauges showed a positive impact (bias = -0.96 mm and RMSE = 6.7 mm). The case study conducted on December 16, 2016 revealed substantial improvements in the precipitation structure and intensity with reference to African Rainfall Climatology version 2 (ARC2) precipitations. Several national weather services around the world produce QPEs based on radar and other data sources like **gauges**, **satellites**, and **NWP** models.

Case Study

In Morocco, the Moroccan national meteorological service in Khouribga City implemented the first weather radar in 1985. Since 2013, the meteorological service has modernized its weather radar network and it now runs six single-polarization C-band Doppler radars and one dual-polarization C-band Doppler radar . All the radars operate at a **range of 250 km**, where the radar network enables nowcasting of weather phenomena related to precipitation. Moreover, for **QPE**, the service has deployed Moroccan weather radars. However, there is an **underestimation** of the radar QPE when compared to the rain gauge network. Additionally, other weather radar networks worldwide have observed this **radar measurement deficiency**. Consequently, one should recognize that a comparison between rain gauges and radar QPEs is not a trivial topic.

First, rain gauges provide amounts relative to point accumulations (around 200 cm2); whilst the radar QPE corresponds to a volume-averaged rainfall rate. **Second**, differences between gauge amounts and radar QPEs not only depend on the quality of radar measurements, but also on the quality of the rain gauge data and the **density of the network**. Therefore, to improve the quality of radar rainfall estimates using a rain gauge depends on good quality gauge data and well-validated merging methods.

So, we must present an approach for radar **rainfall estimation** using the Moroccan C-band radar. First, the radar reflectivity was quality controlled to filter clutter and to correct signal attenuations. Following that, we applied a **mixed adjustment model** combining radar rainfall and gauge measurements. The case study also applied the method to 10 rainfall events from November–December 2016, and in January 2017. This period corresponded to the winter season—being the rainy season—characterized by an arid to semi-arid climate, with the average annual precipitation ranging from 200 to 500 mm. To be continue:

- Radar and the gauge network
- Data processing and mixed adjustment models
- Results and conclusion
- future areas for development

- Radar and the gauge network

The radar data used in the current study were from an operational **single-polarization C-band Doppler radar** located in Khouribga City (Figure 5-7). See Table 5-1 for further details. The radar data are used for nowcasting and posterior analysis of extreme weather events over the plains in both the north and west areas of the radar. The southeast area of the radar is covered by the Atlas Mountains, which causes a severe beam blockage. Since the estimation can be very inaccurate at large distances from the radar, a maximum range of 150 km was used.

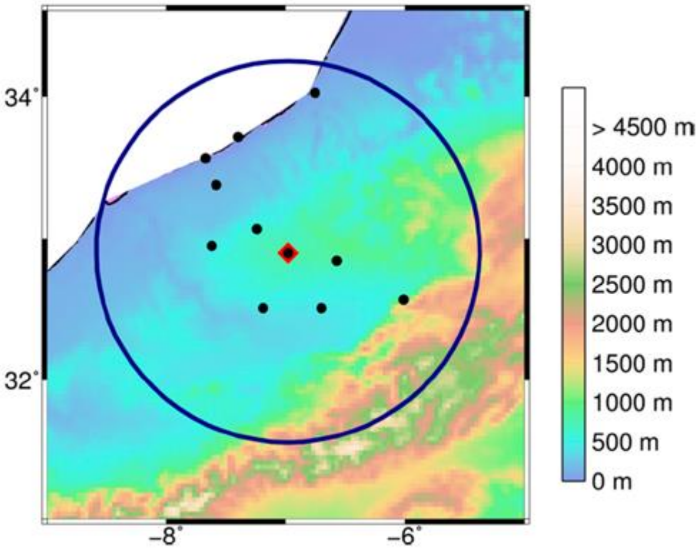

Figure 5-7. Study area, including orography. The blue circle represents Khouribga City's radar coverage at 150 km, the red diamond refers to the radar's location, whilst the black dots indicate rain gauges location.[7]

Table 5-1. Technical specifications of the Khouribga City radar.[7]

Parameter	Value
Latitude	32.85° N
Longitude	6.95° W
Height	774 m
Frequency	5.67 GHz
Pulse repetition frequency	200 Hz
Beam width	1°
Maximum range	250 km
Wave length	0.053 m
Elevations	0;0.5;1;1.5;2;3;4;9;15;20°
Scanning interval	10 min

The study area comprised a gauge network containing 11 stations, as shown in Figure 5-7. A 24 h rainfall amount, cumulated from 06:00 UTC day D to 06:00 UTC day D+1, was provided by six **synoptic stations** and five **automatic weather stations** (Figure 5-7). As for the synoptic stations, the rain amounts were measured by an automatic rainfall sensor (**AKIM** or **CIMEL**), then validated by the collocated **tipping bucket mechanical rain gauge** (Precis Mécanique). The data from the automatic weather stations (Metservice) underwent a quality check that consisted of applying climatological thresholds according to the meteorological situation and consistency analysis with the data from surrounding stations. The reception area varied between 200 cm^2 and 400 cm^2, while the resolution varied between 0.1 mm and 0.2 mm.

- Data processing and mixed adjustment models

In fact, Weather radars indirectly measure the power (received power Pr [W]) of the electromagnetic signal back scattered (reflectivity: Z) by raindrops to the radar antenna. Both the radar reflectivity Z and rainfall rate, R [mm h^{-1}], are functions of the raindrop size distribution (N(D), function D: drop diameter with v is drop terminal velocity).

5-18
$$\mathrm{Pr} = \frac{C}{r^2} Z$$

5-19
$$Z = \int_0^{Dmax} N_0 e^{-\Lambda D} D^6 dD$$

5-20
$$R = \int_0^{Dmax} N(D) \left(\frac{\pi D^3}{6}\right) v(D) dD$$

r [m] is the range from the radar, C [Wm^5 mm^{-6}] is the radar constant and Z [mm^6 m^{-3}] is the reflectivity.

Therefore, the **relationship between Z and R** is assumed to follow a power law, as expressed by Equation (5-21):

5-21
$$Z = a * R^b$$

The coefficients a and b depend on the raindrop size distribution. Different sets of these coefficients were empirically calculated by former studies according to the meteorological situation and the hydrometeor type (e.g., rain, snow or hail).

- Quality control of radar reflectivity (Fig 5-8)

The tool wradlib (https://wradlib.org) can used to process data. This tool contains a number of programs that treat radar data for hydrological and meteorological applications. The quality control process consisted of the **Clutter detection** and **filtering** and **Correction** of **signal attenuation**.

Clutter detection and filtering: Gabella and Notarpietro proposed an easy-to-implement method based on a two-step algorithm. The **first step** consists of verifying the spatial consistency for each pixel according to its neighborhood, due to the fact that noisy echoes usually have larger spatial variability compared to the precipitation field. The **second step** is a test of compactness based on the difference between clutter and rain area/perimeter characteristics. This method produces satisfactory results for C-band radars no matter what the weather conditions are.

Correction of signal attenuation: The main cause for systematic underestimation of radar rainfall is the attenuation of the radar signal by raindrops, especially in cases of **heavy rain**. The current study used Kraemer and Verworn's **gate-by-gate approach** for attenuation correction. This method required no additional inputs (e.g., microwave links or mountain returns) other than the radar reflectivity. The attenuation for the first gate was calculated using the K–Z relationship, Equ. 5-22:

$$K_0 = \alpha * Z^{\beta} \tag{5-22}$$

The attenuation K_0 was then used to increase the reflectivity of the gates beyond. For a given gate, i, K_i is calculated using the reflectivity Zi and the sum of the attenuation from previous gates Equ. 5-23:

$$K_i = \alpha * \left(Z_i + \sum_{j=0}^{i-1} K_j \right)^{\beta} * 2\Delta r \tag{5-23}$$

where Δr = 1 km is the gate length, and coefficients α and β are calculated in real time.
First, the "initial guess" values of $1.67 * 10^{-4}$ and 0.7 were given to α and β , respectively, which generally produced an overestimation of the attenuation . Then, an iterative algorithm was applied to calculate the optimum of the coefficients. This method was efficient and did not require any further independent reference for α and β calculation.

Z-R conversion: Due to a lack of information about the hydrometeor's type and the raindrop size distribution of Khouribga City's radar, multiple combinations of a and b were tested, especially those used for the U.S.Weather Surveillance Radar 1988 Doppler (WSR-88D). The comparison with rain gauges showed that the values a = 75 and b = 2 were the most reliable coefficients for the studied rainfall events.

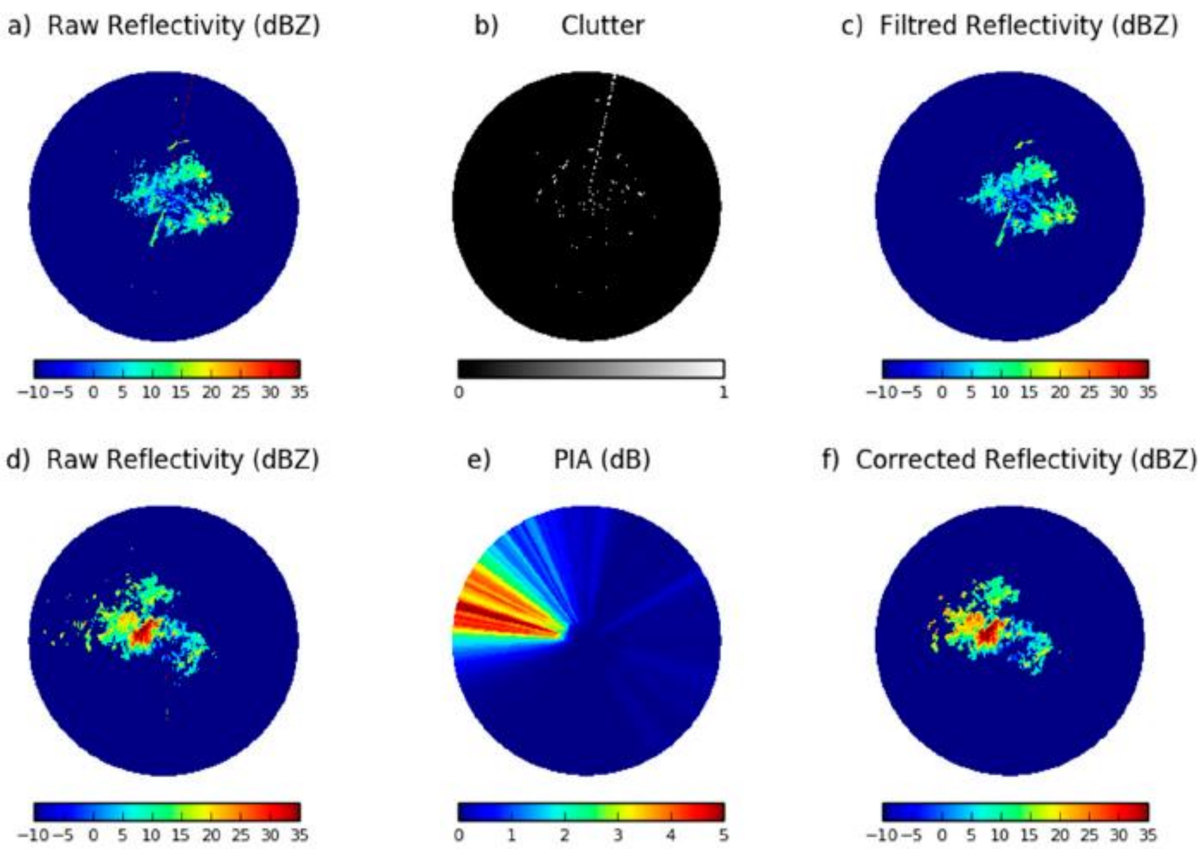

Figure 5-8. (**a**) Raw, (**b**) cluttered and (**c**) filtered reflectivity pertaining to December 16, 2016 at 08:30 UTC; (**d**) raw, (**e**) path integrated attenuation (PIA) and (**f**) corrected reflectivity pertaining to December 17, 2016 at 02:20 UTC.[7]*

*Over the study area, the surface altitude varied considerably between the northwest coastal zone, characterized by its lower altitude, and the mountainous region at the southeast. The use of a lower Constant Altitude Plan Position Indicator (CAPPI) would increase the masked area, while the use of a higher CAPPI might worsen the overshooting problem. Consequently, instead of using radar CAPPI at a fixed level, a **MAXI-CAPPI** was produced. This could be achieved by projecting the vertical maximum of the 3D cumulated rainfall field in a horizontal plane (considered as radar-only QPE).[7]

- Gauge adjustment model (Radar–Gauge Merging Method)

The gauge adjustment performed here used a mixed error model. This model assumes that the error ($R_{gauge} - R_{radar}$) has mainly multiplicative (δ) contributions for large errors. The additive term ε is used in case of a small difference between the radar and the gauge:

$$R_{gauge} - R_{radar} = \delta * R_{radar} + \varepsilon \quad (5\text{-}24)$$

The technical implementation is based on a **least squares estimation** of δ and ε for each rain gauge location by minimizing the sum ($\delta^2 + \varepsilon^2$). Therefore:

5-25 $$\varepsilon = \frac{R_{gauge} - R_{radar}}{R^2_{radar} + 1}$$

5-26 $$\delta = \frac{R_{gauge} - \varepsilon}{R_{radar}} - 1$$

5-27 $$\delta_p = \frac{\sum_{i=1}^{N} \frac{1}{d_i} \delta_i}{\sum_{i=1}^{N} \frac{1}{d_i}}$$

5-28 $$\varepsilon_p = \frac{\sum_{i=1}^{N} \frac{1}{d_i} \varepsilon_i}{\sum_{i=1}^{N} \frac{1}{d_i}}$$

Using an inverse distance weighting, the coefficients are then interpolated to the other Pixels p in (Equations (5-27) and (5-28)). where d_i is the distance between the radar pixel p and the i_th rain gauge, while N is the number of rain gauges.
Finally, at the p_th pixel, the adjusted radar QPE is given by Equation 5-29:

5-29 $$R_{adj} = \left(1 + \delta_p\right) * R_{radar} + \varepsilon_p$$

- Validation of the Adjusted Radar Rainfall Estimate

Based on raw **reflectivity** with no clutter elimination or attenuation correction, Figure 5-9a shows clutter caused by WIFI creates two spokes of unrealistic precipitation (QPE) (120 mm max) that after applying the Gabella filter, this noises was eliminated (Fig 5-9b).

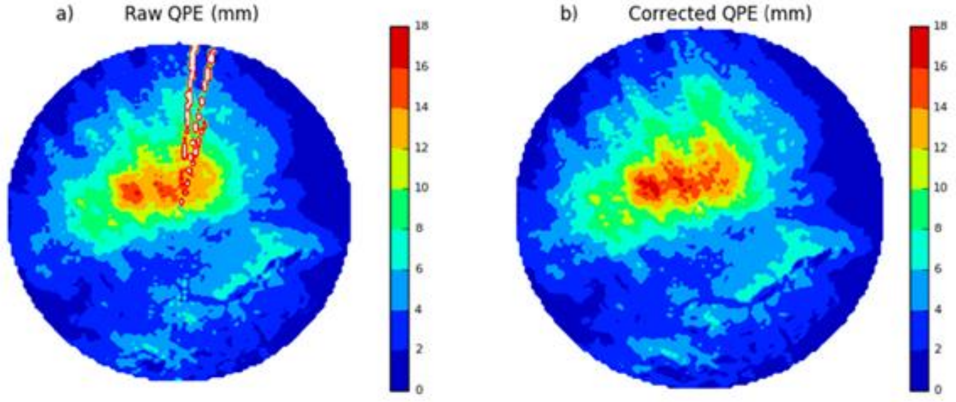

Figure 5-9. (**a**) Raw and (**b**) corrected radar quantitative precipitation estimation (QPE) from December 16, 2016 at 06:00 UTC to December 17, 2016 at 06:00 UTC [7]

Although the attenuation correction strengthened the precipitation cells locally (**near the radar**), as shown in Figure 5-9b, there was no substantial correction for the areas in the northeast sector, where rain gauges reached an amount of 35 mm at Rabat City (130 km distant from the radar). "This was probably due to the small amount of precipitation near the radar"[7]. Considering the stratiform precipitations studied were mainly generated at low altitude, underestimation of precipitation by the radar QPE could be due to **overshooting** or partial filling of the radar beam. In addition, the beam width is about 2 km at 130 km, which can reduce the reflectivity detected in the scan volume and consequently cause underestimation.

Radar-only QPEs (24 h) were firstly retrieved from the **quality checked reflectivity** results for the studied events and then used in the **adjustment model**. For adjusting purposes, the radar rainfall estimate should be calculated at the gauge point. As such, the nearest nine grid points to the gauge location were selected for the radar-only QPEs. The median from this sample was considered as the radar estimated rainfall.

The radar QPE, before and after adjustment, was compared to the rain gauge for 10 rainfall cases. This comparison raised difficult issues; in addition to the quality of both the radar and the gauge's data, numerous factors had an important contribution. The gauge gave measurements of the **surface precipitation** over an area of about **200 cm2**, while the radar estimated the mean precipitation amount of the **upper levels** of the atmosphere over a **6.25 km2 pixel**. Other factors could also be taken into account, such as the **precipitation structures**, the **terrain specifications** and the **wind-drift** effect.

The study area was covered by 24 h cumulated precipitations provided by 11 rain gauges. The gauge network was used for adjustment with no available additional gauge data for independent validation. Assessment of the quality of the **adjusted QPE** was performed using a **cross-validation**. For each event, a "**leave-one-out**" **approach** was applied, which meant that one rain gauge was considered as the test case and removed while the adjustment was performed using the remaining gauges. The adjusted QPE was then evaluated on the removed gauge. This procedure was repeated for each of the available gauges.

To quantify the estimation error, the root mean square error (RMSE) and the bias error were calculated as follows:

$$\text{RMSE} = \frac{\sqrt{\sum_{i=1}^{N}\left(R_{radar} - R_{gauge}\right)^2}}{\text{N}} \tag{5-30}$$

$$\text{Bias} = \frac{\sum_{i=1}^{N}\left(R_{radar} - R_{gauge}\right)}{\text{N}} \tag{5-31}$$

Figure 5-10 shows the scatter plots of the dispersion of 24 h radar-only QPE (Figure 5-10a) and the cross-validation of the adjusted QPE (Figure 5-10b) versus the rain gauges for all studied events. The radar-only QPE usually underestimates the gauges with a bias of -6.4 mm (37% within a distance of 50 km) and a RMSE of 8.9 mm. The use of the **radar–gauge merging method** brought a substantial improvement. In fact, the cross-validation of the adjusted QPE showed a reduction of the bias to -0.96

mm and RMSE to 6.7 mm.

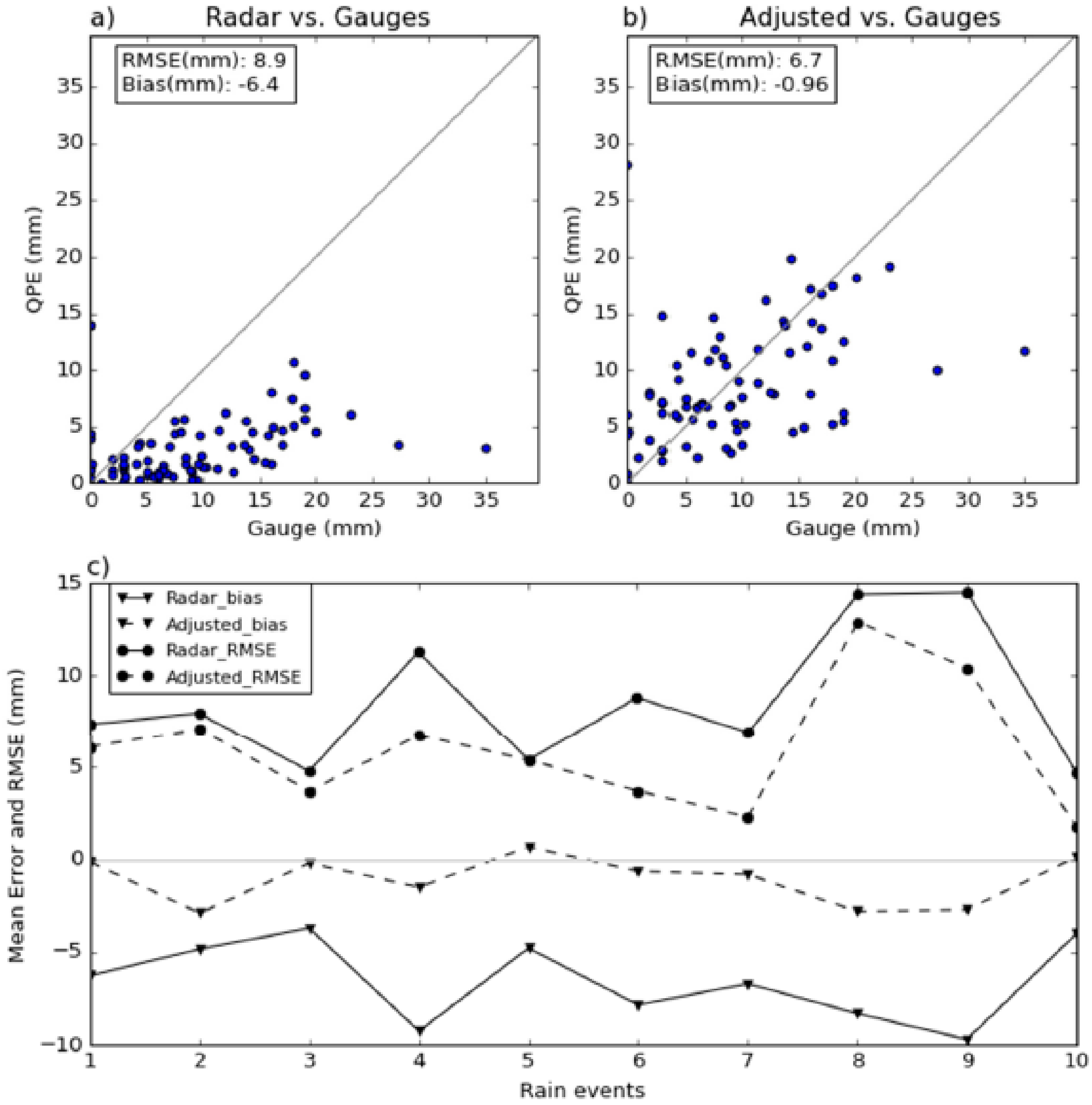

Figure 5-10. Statistics plot of 24 h radar QPE [7]

Case-by-case error statistics (bias and RMSE) for cross-validation of the radar-only QPE and the adjusted QPE are presented in Figure 5-10c. Accordingly, the bias was considerably reduced for all the studied cases. There was also a RMSE improvement for almost all the cases. The enhancement was clear for cases with large errors, such as in 4, 6, 8 and 9. In fact, these events were characterized by an important precipitation amount, especially for gauges more than 100 km from the radar.

- Case study

To assess the effective impact of the adjustment method, the 8th case (held on December 16, 2016) was deeply investigated. The 24 h rainfall amounts measured by the rain gauges (R_gauge), as well as the radar-only QPE (Rradar), are shown in Table 5-2.

Table 5-2 Rain gauge measurements, 24 h radar-only QPE and adjusted QPE cross-validation at different gauge locations for December 16, 2016.[7]

Gauge Location (Cities)	Distance from Radar (km)	Gauge (mm)	Radar-only QPE (mm)	Adjusted QPE Cross-Validation (mm)
Khouribga	2.5	18	10.7	5.2
Casablanca	104	18	5	17.5
Mohammedia	105	20	4.5	18.2
Nouasseur	82	23	6.1	19.1
Rabat	134	35	3.2	11.7
Settat	63	19	9.6	12.6
Ouad Zem	68	16	8	7.9
Benhmed	36	0	14	28.2
Elbrouj	44	0	3.9	4.2
Ksiba	104	19	6.6	6.2
Fquih Ben Salah	44	0	4.4	6.1

The radar-only QPE generally **underestimated** the rainfall detected by the rain gauges. The distance from the radar increased the underestimation—most notably in the case of Rabat City, located 134 km from the radar.

This improvement was specifically remarked upon for the northwest sector of the radar, which was covered by homogeneous precipitations. However, for some gauges, the cross-validation of the adjusted QPE did not reveal a positive impact; for example, in Khouribga and Benhmed cities. This finding was essentially due to the discontinuous aspect of the precipitation field and the impact of the surrounding gauges.

An independent validation was required to evaluate the relative performance of the proposed radar gauge merging method. This validation was performed, taking as reference the African Rainfall Climatology version 2 (ARC2) 24 h cumulated precipitations produced by the Climate Prediction

Centre (CPC) of the U.S. National Oceanic and Atmospheric Administration (NOAA).
As described by Novella and Thiaw, ARC2 daily precipitation analysis is based on several input sources, specifically rain gauges and **geostationary satellite** data. Daily binary and graphical output files are produced with a resolution of 0.1^0, covering Africa from 40^0 south to 40^0 north and from 20^0 west to 55^0 east. Validation with independent gauge data shows that the ARC2 precipitations have an efficient quality and can be used to characterize rainfall events over Africa.
For the studied event, unlike the automatic weather stations, the rain data from synoptic stations were included in the ARC2 precipitations Fig 5-11.

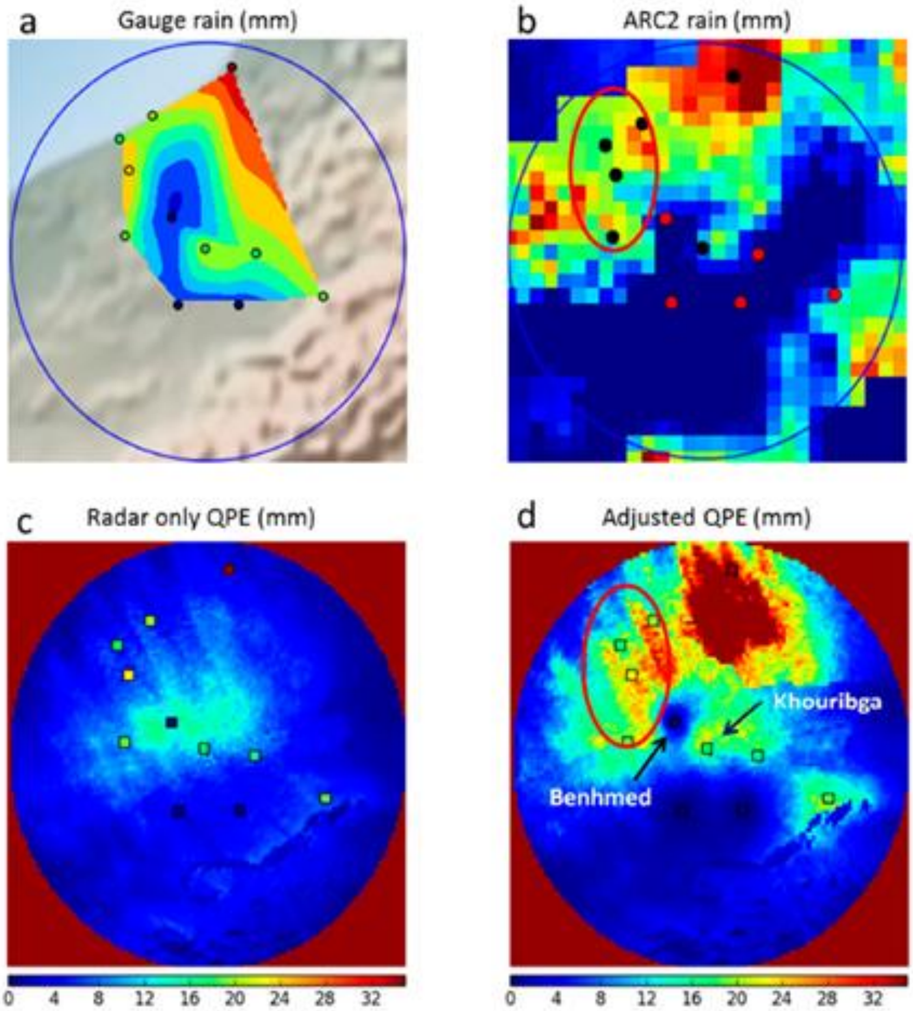

Fig. 5-11. 24 h cumulated precipitations (mm) from December 16, 2016 at 06:00 UTC to December 17, 2016 at 06:00 UTC. (**a**) Interpolation of the rain gauges, and (**b**) African Rainfall Climatology version 2 (ARC2) daily precipitation. The black circles are synoptic stations while the red ones are automatic weather stations. (**c**) Radar-only QPE, and (**d**) adjusted QPE. The squares represent the rain gauges location colored according to the observed precipitation amount.

Figure 5-11 presents the validation of the precipitation field regarding the ARC2 data, and shows that the field produced by a linear interpolation of the gauge data (Figure 5-11a) gave local information, but was unable to reproduce the precipitation structure over a larger area. The radar-only QPE (Figure 5-11c) strongly underestimated the rainfall amounts. As for the adjusted rainfall field (Figure 5-11d), it generally matched the ARC2 data (Figure 5-11b). In fact, spatial structures and precipitation amounts were improved after adjustment.

The adjustment helped to reproduce precipitation cells of more than 20 mm that were present in the ARC2 product (red ellipses in Figure 5-11b,d). The adjustment was also useful in strengthening the precipitation amounts, especially in the north of the radar area. Thanks to its high resolution (2.5 km against 10 km for ARC2), the adjusted QPE showed small-scale structures that could not be identified in the ARC2 rain field. However, an overestimation was observed due to the 35 mm rain gauge (Rabat City) and the lack of other surrounding rain gauges. At first glance, the 0 mm observed in Benhmed appeared to be unrealistic. However, the 0 value is coherent with the ARC2 field (Figure 5-11b) that did not include this rain gauge in its analysis. The overestimation by the radar QPE was probably due to the use of MAXI-CAPPI.

The southeast sector of the radar was masked by the Atlas Mountains, which created a beam blockage and prevented a satisfactory detection of the precipitation over this area. The merging method was unable to deal with such phenomena, especially with the dearth of gauge observations over the mountains.

- Discussion and Future areas for development

The current methodology aimed to improve the rainfall estimation based on Moroccan weather radars. However, the study of rainfall events over November-December 2016 and in January 2017 showed an underestimation of the radar-only QPE according to the rain gauges. The attenuation correction alone was unable to sufficiently strengthen the precipitation cells far from the radar (>100 km) since, in all studied cases, there were only light to moderate precipitations near the radar.

The underestimation was probably due to an overshooting problem of winter stratiform precipitations, mainly generated at low altitude.

The adjustment based on a mixed model produced improved radar QPE, as shown by the cross-validation of the adjusted QPE versus gauges. The detailed study of the events of December 16, 2016 showed the positive impact of the gauge adjustment and also the sensitivity of the results to the density of the gauge network.

A comparison with ARC2 precipitation analysis revealed that the adjustment method had a positive impact on the precipitation structure and intensity. Indeed, the precipitation cells generally fitted the ARC2 field, especially in the northwest sector, despite an overestimation found near Rabat City due to the lack of surrounding gauges. These findings agree with former studies in similar conditions [7], which also showed a better quality and a relevance of the hydrological applications of adjusted rainfall radars when compared to rain gauges, raw radars or satellites precipitation estimations.

These promising results may certainly be enhanced by the use of a high density gauge network, especially for spatially-discontinuous rainfall events. More case studies should be performed to thoroughly investigate the impact of different hydrometeor types, such as snow or hail, associated with snowfall or orographic precipitations over the other regions. In addition, the use of further data sources like satellites and NWPanalysis will doubtlessly bring more accuracy to the adjusted QPE. When it comes to a rough terrain like the study area, merging methods or using orographic precipitation climatology should be tested in order to improve the radar rainfall products, particularly when the constraints are specifically related to the orography [7].

5-2-2 Radar rainfall in urban hydrology

This section focus on abstraction of roadmap for use of weather radar rainfall data in urban drainage which was published in Journal of Hydrology by Einfalt et al, 2004 and data processing, as well as methods and challenges in urban water cycle (flood prone areas, prediction, climate change impacts, resilience of urban systems to hydrological extremes, groundwater interaction, rivers, and online prediction/warning systems) based on Thorndahl, et al research, 2017.

Climate change and consequently increase in extreme rainfall have been a significant catalyst for the development in urban hydrological models as well as radar technology. So it is vital to accommodate climate change and develop integrated hydrological models (integrated urban drainage, river and inundation models) to simulate urban flood risks and manage **uncertainties** based on to fully utilize the capacity of drainage systems or nowcasting of rainfall to manage of combined sewage flow in urban drainage systems. The use of more detailed and distributed models increased the demand for good **quality, and high resolution inputs** in radar data in urban hydrology. So spatial and temporal scales sufficiently require, although the errors in radar data are one of the most important sources of uncertainty in (urban) hydrological models (section 5-2-1).

For example in a sewer system model in Belgium was shown by Willems and Berlamont (1999) that about 20% of the total uncertainty in the downstream sewer throughflow debits could be explained by the rainfall spatial variability and about 20-25% by the rainfall measurement errors, consisting in their case of rain gauge calibration errors, rainfall intensity resolution errors and errors by wind and local disturbances. For extreme events, e.g. flash flooding, uncertainties related to spatial variability and rainfall measurement errors are expected to be even larger (Bene et al., 2004; & etc.). Daliri and Kholghi (2010) showed effects of the storm time distribution and initial loss in rural flood modeling (SCS-CN) could have total erros more than 50%. We know urban flood is characterized by fast runoff and short response times on impervious surface and thus small timescale and space scales compared to rural hydrology. Hence there is a need for high quality and high resolution rainfall inputs into urban hydrological models in order to reduce uncertainties for hydrological responses. So, **adjusted radar data** (section 5-2-1) are vital and ideal in that respect, although development of signal processing and software-hardware in radar technology, based on atmosphere physics, e.g. antenns, frequencies, bandwidths, polarization, data correction, e.g. attenuation, clutter removal, and reflectivity-rainfall conversion equired. Many researchers such as Marshal and Palmer (1945), … Berne and Krajew-ski (2013) provide general imformation on radar rainfall. Also **VDI** (2014), and **ISO** (2017) have produced a standard on precipitation measurement by radar.

Table 5-3. Typical operating resolutions and maximum ranges for different types of weather radars used in hydrological applications [10]

	X-band	C-band	S-band
Spatial resolution	100–1000 m	250–2000 m	1000–4000 m
Temporal resolution	1–5 min	5–10 min	10–15 min
Maximum quantitative range	30–60 km	100–130 km	100–200 km

Moreover Berne et al. (2004) suggested a relation between the temporal (t in min) and spatial (r in km) resolution of $r = 1.5t^{0.5}$ for Mediterranean rainfall condotions, and Van de Beek et al. (2012) extrapolated this to $r = 5t^{0.3}$ for summer conditions in the Netherlands. The type and severity of a strorm (size, movement, shape, lifespan, intensity, etc.), basin size, and basin characteristics, might effect to select the space-time resolution of radar. A high-intensity convective thunderstorm with small spatial extent in **urban areas** will need a higher resolution in both space and time to be resolved, in contrast a stratiform long-duration storm in **large rural areas**.

To be continue three key areas and relevant applied topics, readers linked to [10].
-Resolution of radar data (table 5-3)
-Rainfall estimation, radar data adjustment and quality
-Nowcasting of radar rainfall and real-time applications
-Other relevant applications of radar in urban hydrology

5-2-3 NWP rainfall forecasting

Unknow future precipitation is the dominant source of uncertainty for many streamflow forecasts. Numerical weather prediction (NWP) models can be used to generate quantitative precipitation forecastse (QPF) to reduce this uncertainty. For streamflow nowcasting (very short lead time, e.g., 12 h) many application are based on measured in situ or radar-based real-time precipitation and/or the extrapolation of recent precipitation patterns but QPF based on NWP models output may be more useful in extending forecast lead time, particularly in the range of a few days to a week, although low NWP midel skill remains a major obstacle [12]. Main topics, in this section are:

- Review of NWP models
- Introduction to ensemble QPF methods and streamflow forecasting techniques
- Integrated systems that use NWP model output to force hydrologic models
- Issues of spatial scale and initial conditions (section 5-2-2 & 5-2-1)
- Identify of operational integrated systems (section 5-3-1)
- Characterization of uncertainty and the role of ensembles (section 5-3-1)

NWP models use current weather conditions as input to atmospheric models to predict the evolution of weather systems through the use of mechanics and thermodynamics. NWP model output **ensembels** have been generated since the early 1990s (e.g., ECMWF ensembles started in 1993) and **probabilistic** weather forecasts have been used to articulate forecast uncertainty.
In ensemble forecasting, one or more dimensions of forecast uncertainty are explored through the use of scenarios. There are many ways to categorize ensembles. Ensembles methods classify based on[12]:

- **Number** of models used. Some ensembles combine deterministic forecasts from multiple models (Hagedorn et al., 2005).
- **Single model** with perturbed initial conditions, boundary conditions, or parameters (Toth and Kalnay 1993).

(The ensemble **members** must represent the probability distribution of the state of atmosphere and improve the ensemble forecast skill compared to the control forecast. Toth and Kalnay (1997) found that only a minimal improvement in ensemble forecasts is obtained beyond 20 members. However, they also found that there was still much to be gained in the temporal and spatial relationship between spread and error by increasing the size of the ensemble beyond 40 members)

- "**Grand**" or "**super**" ensemble, a collection of ensembles from individual models (Krishnamurti et al. 1999; park et al. 2008).
- "**lagged ensembles**", to use forecasts (ensemble or deterministic) from other lead times for the same target period to form what has been called " lagged ensembles" (Mittermaier 2007).
- Ensemble QPF from **data extrapolation**, and **blended/hybrid** products. For instant, radar, satellite, NWP model forecasts, and in situ rain gauge data can be blended statistically. This can improve the reliability of the forecasts in the very short term, (geographic coverage of satellite, improve the spatial-temporal resolution of NWP model outpu.

Persistence- and extrapolation –based forecasts can be better than NWP models at shorter lead times. At longer lead times, the initial conditions wash out and NWP models become the most reliable source for information (Zipser, 1990). Blended products ensure that the best available information is used at each lead time. Therefore, blending is an important component of very short lead time (<12 h ahead) "nowcasting" forecasting systems. Nowcasting is a technique for very short-range forecasting that maps the current weather and then uses an estimate of its speed and direction of movement to forecast the weather a short period ahead (usually 0-7 h lead time) based on current or most recent observations. Examples of such blended nowcasting QPF are the U.K. Short Term Ensemble Prediction System (**STEPS**; Bowler et al. 2006) and Ganguly and Bras (2003).

Large events are more predictable and small events have a shorter lifetime. Information from an NWP model is used to extrapolate or propogate larger precipitation features, whereas the smaller events are filled using a statistical method. Many scenarios are generated to represent various moving speeds for large events and different random statistics for small events. Active research has been undertaken to extend the forecast lead time by integrating radar and satellite data (Golding 2000).

Streaflow forecasting methods include conceptual, physical, statistical, routing, etc. that described in prior chapters. Some of these models, accept precipitation and potential evapotranspiration (PET) as forcings, calculate losses to actual evapotranspiration, simulate the changes in surface and deeper soil moisture, and produce runoff. Oudin et al. (2006) found that, while sensitive to systematic errors in PET, hydrologic models are relatively insensitive to random errors in PET; it is often sufficient to assume that PET over the forecast horizon is the same as the long-term historical average. Therefore, the main streamflow forecasting challenge is to estimate the moisture in catchment soils by using recent measured precipitation and predicted future precipitation. The catchment may be **lumped**, in that a single time series of catchment average precipitation forces the model. It may be **semidistributed** in that the subbasins are represented as irregulaely shaped but hydrologically homogeneous. **Distributed** models also relate model parameters to fields of soil characteristics and other physical properties, commonly on an evenly spaced grid (which is most similar to NWP models). Around the world, the most common forecasting method uses a combination of real-time precipitation and streamflow gauge data (some cases radar, satellite data, and NWP model); forecasts are often issued in a deterministic mode.

The U.S. National Weather Service (**NWS**) has generated ensembles using **ESP** method (Ensemble streamflow prediction) for three decades (Schaake 1978). It has been particularly successful in springtime in snowmelt-dominated regions where the initial conditions (snowpack and soil moisture) largely determine the expected volume of flow and the climate scenarios (e.g., temperature) provide a range of possibilities for timing and rate of flow. ESP has been applied in non-snowmelt dominated areas, mostly in combination with seasonal climate (e.g., precipitation) forecasts to determine the likelihood of each ensemble trace (Croley and Hartmann, 1987). In these non-snowmelt dominated areas, ESP has been used for short-range **(<15-day lead time**) operational forecasting.

The forecast ranges are based on WMO definitions:

- Nowcasting range is 0-2 h ahead,
- Very short-range forecasting is 0-12 h,
- Short-range forecasting is 12-72 h,
- Medium-range forecasting is 72-24 h.

Shrestha, et al., 2013, found that it is necessary to remove the systematic biases in NWP rainfall forecasts with Australian Community Climate Earth-System Simulator (**ACCESS**, for four models: **ACCESS-**G with 80 km resolution, **ACCESS-**R with 37.5 km, **ACCESS-**A with 12 km, and **ACCESS** -VT with 5 km), particularly those from low resolution models (relief and lead time is important), before the rainfall forecasts can be used for streamflow forecasting, (Fig 5-12),[13]. Moreover, Na & Yoo, 2019, found that as the lead time increases, the quality becomes even lower. They proposed method considers all available rainfall forecasts as ensemble members at the target time (section5-3-1-1) [14]. The proposed method is tested with McGill Algorithm for precipitation Nowcasting by Lagrangian Extrapolation (MAPLE) rainfall forecasts for four storm events. The quality of the ensemble forecast is also found to be better than of the single forecast.

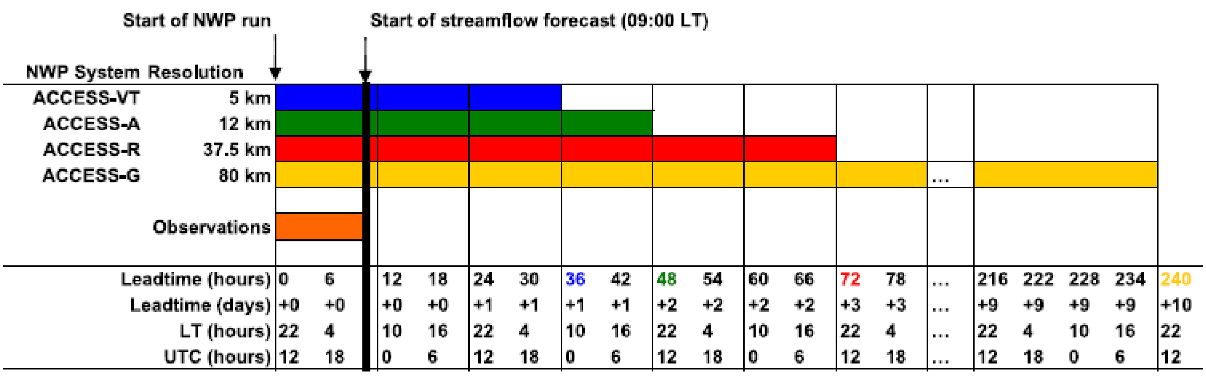

Fig. 12. Schematic of NWP model runs [13]

5-3- Flood forecasting

Computers continue to get more powerful. As a result there is absolutely no doubt that distributed hydrological models will become more detailed, more complex and more closely coupled to geographical information systems for the input of data and display of results [16]. This, in one sense, is the current start of the art. There is a question, however, as to whether this type of development will lead to better hydrological predictions. The answer to this question is not at all clear. More complexity means more parameters; more parameters mean more calibration problems; more calibration problems often mean more uncertainty in the predictions, particularly outside the range of the calibration data. Something that has not changed is that the application of all types of model is limited by the available data on how hydrological systems work.

Models are data constrained because of the strong limitations of current measurement techniques. However, even if improved measurement techniques lead to a better understanding of complex flow processes, it appears that it will be necessary for the foreseeable future to distinguish between models developed for **understanding** (which describe those processes in detail at small scales) and models developed for **prediction** at catchment scales [16], [3], [17,18]. (Chapter2).

Why are New Modelling Techniques Needed?

In considering the next generation of hydrological models, it is important to distinguish between different reasons for modelling. What the next generation model looks like might well be different for different purposes. If the interest is only to show that we "understand our science and its complex interrelated phenomena" then a model structure might look very different to that needed to make flood forecasts at a particular site of interest. Using a complex process model for flood forecasting might not be sensible either in improving the accuracy of predictions or in providing forecasts with sufficient lead time for people to react to a flood warning. In other cases, a model that predicts the fluxes in different flow pathways might be needed. Such models might be used to explore the effects of land management on water fluxes and water quality, for example. There are also increasing demands to understand the links between hydrology and ecology in effecting improvements to the water environment and maintaining biodiversity, demands given impetus in Europe by the requirements of the Water Framework Directive. It seems unlikely that all these different reasons for using models can be met by a single modelling approach in the future. The next generation of hydrological models is likely therefore to continue to be diverse.

How are the REW Concepts Different from Other Hydrological Models?

The difference is in the way in which the REW concepts require that the mass, energy and momentum balance equations are considered in an integrated and consistent way at the scale of a discrete partitioning of the landscape into REW elements. The REW framework is based on physics, in that it sets out the fundamental balance equations for the processes underlying the hydrological response of a control volume element of the landscape.

"A useful background volume is the IAHS Benchmark volume of classic papers in rainfall–runoff modelling prepared by Keith Loague (2010). The volumes edited by Vijay P Singh (1995) and Singh and Frevert (2002a, 2002b, 2005), which collected chapters written by developers of models for large and small catchments, are also valuable sources of information. Distributed models of various types are discussed in the texts by Mike Abbott and Jens Christian Refsgaard (1996), David Maidment (2002) and Baxter Vieux (2004); lumped conceptual ESMA-type models by Thorsten Wagener *et al.* (2004); and linear systems models by Jim Dooge and Philip O'Kane (2003). There are also many relevant articles in the *Encyclopaedia of Hydrological Sciences* edited by Malcolm Anderson (2005), including a section devoted to rainfall–runoff modelling in Part 11 of Volume 3 [16]"

5-3-1 Integrated forecast systems

First, must to mention that some systems do not rely on NWP models while generating very short-term (0-12 h lead times) streamflow forecasts (**non-NWP system**). The general state of the art in the integration of NWP model output and streamflow forecasts showed in Fig. 5-13.

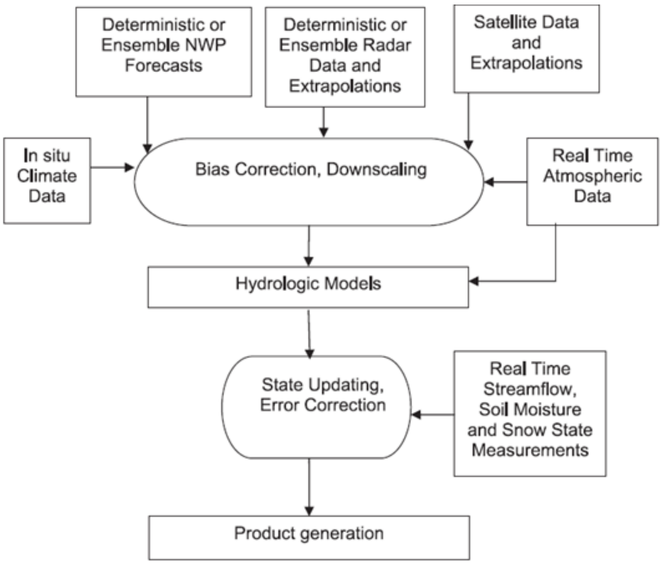

Fig. 5-13 NWP/radar/satellite-driven streamflow forecast system [12]
In this figure, ''extrapolation'' means a future forecast based on an extrapolation of recent measured patterns, such as is used in STEPS (very short to medium range forecasting)

For example, **SEPA** system uses both measured and forecast radar precipitation and lumped Probability Distributed Moisture (PDM) hydrologic model for flash flood forecasting through the U.K. Nimrod system. Results show that Nimrod's precipitation predictions are uncertain and sometimes biased, although there is considerable benefit in their use for flood forecasting compared to not using precipitation forecasts [12].

Roberts et al. (2009) and Jasper et al. (2002) pointed out that radar coverage is often incomplete because radar scans are too high to see low-level precipitation, or because of ground clutter and beam blockage in rugged terrain. In this situation, high-resolution NWP model simulation can be used to fill the gaps, making such blended NWP model/radar systems more robust than single-source systems. For systems that use deterministic NWP model/radar and other information, an example is the U.K. real-time flood forecasts issued by the Environment Agency in collaboration with the UKMO (Golding 2009). **Real-time precipitation, river level/ flow, sea level, and measured radar data** are used to initialize the hydrologic model. Six-hour-ahead radar **extrapolation** and raw output of forecast precipitation from UKMO NWP models are used as QPF for the hydrologic forecasting models. The skilful lead time of the hydrologic forecasting system varies from 1–12 h across the United Kingdom depending on the distance to the coastal area. Japanese hydrologists combine NWP model output products and radar-based precipitation information to provide streamflow forecasts at 6 h lead times[12].

"(The Mesoscale Alpine Programme's Demonstration of Probabilistic Hydrological and Atmospheric Simulation of Flood Events in the Alpine Region (MAP D-PHASE) project issued streamflow forecasts using radar information and deterministicNWPmodel forecasts for the summer and autumn of 2007. France establishedthe National Hydrometeorological Service (SCHAPI) to develop techniques for merging short-range forecasts from radar-based techniques and NWP models, and to assess the ensemble precipitation forecast uncertainty for nowcasting. Other similar forecasting systems include the U.S. Gridded Flash Flood Guidance system, Central American Flash Flood Guidance system, Northern Austria Flash Flood Forecast system, Thailand Decision Support System for Flash Flood Warning, the Geospatial Data Exchange System (GEOREX) flood forecasting system of Malaysia, and systems in place in Germany and the Republic of South Africa (see more details in Hapuarachchi et al. (2011))"

For short- to medium-range forecasts (12–240 h), the integration of NWP and hydrologic models has been a focus of the research community and there has been relatively less operational adoption. For example, Clark and Hay (2004) used 40 years of eight-day atmospheric forecasts over the contiguous United States from the National Centers for Environmental Prediction (**NCEP**) reanalysis project to assess the possibilities for using the Medium-Range Forecast (**NCEP–MRF**) model output to aid predictions of streamflow. They concluded that NCEP–MRF output must be preprocessed before it is used for hydrologic predictions because of the **systematic precipitation biases** (exceeding 100% of the mean) and temperature biases (38 c^{o}) [12].

They used a model output statistic (**MOS**) technique to downscale the NCEP forecasts to station locationsand a forward screening multiple linear regression model to improve forecasts of precipitation and temperature. After preprocessing, Clark and Hay's temperature forecasts were improved while precipitation forecasts were mixed. Eight-day streamflow forecasts produced using the MOS-corrected NCEP–MRF output were compared with those produced using the climatic ESP technique. They found that MOS-corrected streamflow forecasts had the most skill in snowmelt-dominated basins where temperature is the major factor. In rainfall-dominated basins, MOS-corrected streamflow forecasts were no better than those from the ESP method, primarily because the original forecasts of precipitation were poor.

Habets et al. (2004) used QPF from two French NWP models as inputs to a hydrologic model. The QPF used in their study underwent statistical correction or regional adaptation to correct errors. By comparing forecasts in which the initial state was **randomized** versus forecasts in which the initial state was obtained by using **recent measured** precipitation and temperature, they found that streamflow forecasts in this region were very sensitive to the initialization of soil moisture and snowpack. They found **systematic biases** in precipitation amount (on the order of ;20%) and phase (rain versus snow).

Rabuffetti and Barbero (2005) described the development and implementation of a **real-time flood forecasting system** with a lead time of 48 h in the Piemonte region of Italy. The forecasting system is composed of **survey, warning, alarm, and emergency phases**. The operational FloodWatch, a geographical information system (GIS)- based decision support system (**DSS**) for real-time flood survey and forecasting, was established in 2000, and is a 24-h operating service. The information that feeds into the system includes telemetered meteorological and hydrologic gauge data, two weather radars, weather forecasts at local and global scales (NWP), and hydrologic modeling for flood forecasting on the main river network. They find that NWP model outputs allow warnings with lead times needed by the civil protection agencies; use of NWP model output also introduces many **sources of uncertainty** so that the deterministic simulations need careful interpretation. Many studies reported that NWP model outputs introduce significant uncertainty into hydrologic modeling. Georgakakos and Hudlow (1984), Damrath et al. (2000), Ebert and McBride (2000), Habets et al. (2004), Ebert et al. (2007), and Lu et al. (2010) all stated that QPF quality needs to be improved to provide reliable hydrologic prediction. Errors in QPF location, timing, and intensity hampered the direct QPF application to hydrologic prediction.

Ensemble forecasts attempt to quantify this uncertainty and this is the focus of the remainder of this section[12]:

5-3-1-1 Characterization of uncertainty and the role of ensembles

This subsection describes the various sources of uncertainty in streamflow forecasts. The purpose is to show that the common strategy of using ensemble forcings is not a complete representation of uncertainty[12]. The full spectrum of hydrologic prediction uncertainty includes several aspects:

1) model input data such as precipitation and temperature uncertainty;
2) model initial conditions such as soil moisture, snow, and river flow uncertainty; and
3) hydrologic model uncertainty due to its physical representations and parameter uncertainty.

To account for the full range of uncertainty, Schaake et al. (2007) listed the main elements of hydrologic

ensemble prediction system; these are:
1) an atmospheric ensemble preprocessor,
2) a data assimilator,
3) an ensemble of hydrologic models,
4) a hydrologic ensemble processor, and
5) a forecast product generator.

There have been studies about the individual aspects of uncertainty along this chain (Chain of uncertainty). Many studies have been done on the accuracy of NWP model forecasts in predicting precipitation, such as Houtekamer et al. (1996), Stensrud et al. (1999, 2000), Ebert and McBride (2000), Bright and Mullen (2002), Sattler and Feddersen (2005), and Ebert et al. (2007).

Several authors have then carried through NWP model uncertainty into the hydrologic forecasts, such as Kobold and Susˇelj (2005), Bartholmes and Todini (2005), Gouweleeuw et al. (2005), Pappenberger et al. (2005), Collier (2009), Xuan et al. (2009) and Mascaro et al. (2010).

In all cases, the hydrologic model results were very sensitive to the forcing data.

Other authors have attempted to isolate the uncertainty components. Krzysztofowicz (1999, 2002) separated **forecast uncertainty** into ''input'' (mainly precipitation) and ''hydrology'' (a blend of model, parameter, and others) uncertainty and then integrated the two uncertainty components into ''forecast'' uncertainty.

A **Bayesian** postprocessor was used to analyze the output component error associated with particular data input types (Collier and Robbins 2008). Carpenter and Georgakakos (2004, 2006) analyzed the influences of precipitation input and hydrologic model parametric uncertainty on the flow simulation uncertainty. They found that, when using radar data, flow uncertainty is closely related to the catchment scale. Collier (2009) found that the error in weather radar precipitation data propagates through a fully distributed model. To account for the short-term precipitation errors, Collier (2009) used short-range ensemble precipitation forecasts.

Efforts to quantify hydrologic (i.e., model parameter, initial condition, and physical representation) uncertainty have had mixed results. For example, Shi et al. (2008) found that an objectively calibrated Variable Infiltration Capacity (VIC) model and noncalibrated but bias-corrected VIC model simulation produced the similar forecast skill scores for seasonal streamflow forecasts. However, without bias correcting, Yilmaz et al. (2005) reported that hydrologic model forecasts forced with satellite-based precipitation data were significantly worse when the hydrologic model parameters were not calibrated to the forcing dataset. Bohn et al. (2010) found in the context of seasonal hydrologic forecasting, multi(hydrologic)-model averaging may be no more effective in reducing forecast errors than applying a monthly bias correction to a single model in snow-dominated basins.

The key objective of investigating the uncertainty chain is to identify the sources of dominant uncertainty and to extract the useful forecast information from the uncertain system and effectively communicate forecast confidence to end users. Unfortunately, the dominant uncertainty is often **basin specific** or **time- or space-scale** dependent. Part of the issue is how few studies have attempted to analyze the total system error, especially the components of hydrologic error (e.g., Krzysztofowicz 1999; Pappenberger et al. 2005).

At times it seems like the only reliable conclusion from the literature is that **QPF uncertainty** is the **dominant source** in a vast array of **hydrologic forecasting** contexts.

To complicate the picture, **hydrologists** have several tools for compensating for uncertainties within the system. In short-range streamflow forecasting, **data assimilation procedures** are often implemented to reduce hydrologic uncertainty. These procedures seek to reduce the difference between the simulated and measured by changing the input forcing (input updating), changing how the model simulates flow (state updating and parameter updating), or simply by postprocessing the output (output updating; Madsen and Skotner 2005). Madsen and Skotner (2005) updated the model parameters for streamflow forecasting, and Bogner and Kalas (2008) used a dynamic linear model to update the model states. Seo et al. (2003) is an example of output, input, and state updating, among many others. Output updating is cost effective and is a commonly used procedure (Sene 2010).

Although such model corrections are effective during forecasting, they can lead to unexpected interactions. For example, output updating may be calibrated on the simulation performance of the hydrologic model. If the real-time forecasts use state updating but this was not used in the historical simulation, are the statistics for the output updating still reliable? Furthermore, forecast errors may be due to deficient models (e.g., poor representation of certain processes); model improvement may be more direct and effective than data assimilation at reducing errors.

Relevant programs of ensemble forecasts

The use of NWP model–based ensembles (section 5-2-3) may be to quantify uncertainty in hydrologic forecasts. However, the common problem in the ensemble forecast system identified by many studies is the inaccuracy of the NWP model forecast itself. In many of these studies a deterministic forecast is included as a control or baseline. The recent research literature has many studies of ensemble streamflow forecasting. Cloke and Pappenberger (2009) is an excellent contemporary review[12].

Ensemble precipitation forecast distribution underdispersion (i.e., **overconfidence**) is also a common complaint. Charges of probabilistic underdispersion have been leveled at ensemble hydrologic forecasts as well, so it may be a universal challenge in ensemble forecasting.

One of the fully operational systems where NWP model–based ensembles are routinely and widely used to generate streamflow forecasts is the European Flood Alert System (**EFAS**; Thielen et al. 2009) in the Joint Research Centre of European Commission and the Swedish Meteorological and Hydrological Institute (**SMHI**; Olsson and Lindstro¨m 2008). All other systems are preoperational or use ensemble QPF episodically and/or for a limited subset of catchments. EFAS incorporates deterministic NWP model output from ECMWF (10-day lead time) and the German Meteorological Service (DWD; high-resolution 7-day lead time). It also uses a full set of 50 ensemble members from ECMWF and a 16-ensemble-member run from the Consortium for Small-Scale Modeling Limited-Area Ensemble Prediction System (COSMO-LEPS). The NWP model results force a spatially distributed version of a **hybrid conceptual–physical hydrologic model** LISFLOOD (de Roo et al. 2000). Ensemble members are run at a 24-h time step, and deterministic forecasts are run at a 1-h time step.

An international initiative to foster hydrologic ensemble prediction science is worthy of mention: the Hydrologic Ensemble Prediction Experiment (**HEPEX**). HEPEX is an open ‘‘international effort that brings together hydrological and meteorological communities to develop advanced probabilistic hydrologic forecast techniques that use emerging weather and climate ensemble forecasts'' (Schaake et al. 2006; Thielen et al. 2008). The objective of HEPEX is reliable quantification of hydrologic forecast uncertainty.

Cloke and Pappenberger (2009) discussed the problems and challenges in short- to medium-range hydrologic ensemble prediction. They identified seven challenges, which are paraphrased here:

1) Current NWP model output skill is low; resolutions are too coarse and too few ensemble members exist.
2) We do not understand the total uncertainty in the system and so will have trouble with extremes.
3) Hydrologic data assimilation is underutilized.
4) Studies rely on too few case studies.
5) There is not enough computer power.
6) There is inexperience with ensembles in operational flood forecasting environments.
7) Communicating uncertainty and probabilistic forecasts is difficult.

When computational power is a limitation, deterministic NWP model forecasts are often a reasonable alternative in order to extend forecast lead time. Another issue that also exists for ensemble systems, but is not emphasized by Cloke and Pappenberger, is how to couple the coarse NWP model [e.g., the 12-km Australian Community Climate and Earth-System Simulator (ACCESS)] forecasts to a smaller-scale hydrologic model (e.g., 5 km). While it might not be necessary to rescale NWP model deterministic forecasts (though bias correction may still be needed), ensemble NWP model output is often at a coarser scale than hydrologic models and would need both downscaling and bias correction. A variety of downscaling methods exist (e.g., Venugopal et al. 1999).

5-3-1-2 Integrated NWP models and hydrologic forecast systems

SELECT A HYDROLOGIC MODEL

The **choice of hydrologic model** depends on the forecast lead time, catchment size, and the characteristics of runoff (Arduino et al. 2005). It will also depend on the operational forecasting center's experience and legacy systems or expected accuracy. Physics-based distributed hydrologic models are more likely to represent the cause–effect relationships leading to changing runoff behavior (Arduino et al. 2005). In the distributed model, flood inundation information across the catchment could be more easily derived. However, the distributed model is usually parameter intensive and there is uncertainty associated with parameters. Furthermore, physics based distributed models still trail behind conceptual lumped models on most performance measures evaluating simulated streamflow at the catchment outlet (Smith et al. 2004). Pagano et al. (2009) evaluated many hydrologic models in order to determine their ability to simulate streamflow and their potential for operational implementation in Australia. Many models performed equally well, although Genie Rural a´ 4 Parametres Journalier (GR4J; Perrin et al. 2004) stood out for its combination of performance and parsimony, having only four parameters [12].

CONSIDER HYDROLOGIC UNCERTAINTY

Parameter uncertainty could be examined by using Pareto sets that are generated during the model calibration (e.g., Pappenberger et al. 2005). If the calibration is trying to satisfy many objectives (e.g., the fit to high flows, low flows, etc.), the Pareto set is the collection of parameter sets that perform the best for a given mixture of objectives. It is unknown if certain parameter sets behave equally well with different forcings such as measured and NWP model–simulated precipitation. **Model structure uncertainty** could be examined using multimodel ensemble approaches (e.g., Nijssen et al. 2003). The simplest way to investigate the **initial condition uncertainty** is to generate model initial conditions based on the historical climate data for particular days and examine the ensemble of hydrologic model simulations using various initial conditions. To compare the uncertainties from all aspects, there should be a common reference (measured streamflow).

REMOVE SYSTEMATIC HYDROLOGIC BIASES

A hydrologic model forced with measured precipitation may be able to simulate measured streamflow well in the calibration period, but may produce biased results in other periods. If **bias** is present and it is systematic, it should be removed by postprocessing.

CONSIDER THE EFFECTS OF HYDROLOGIC DATA ASSIMILATION

Data assimilation can be used to improve hydrologic forecasting skill. Output updating (e.g., Anctil et al. 2003) may be the method of choice because it is cost effective and widely used. In this method, an error-correction forecast model is built based on the measured hydrologic model residuals; predictions of the anticipated error are used to adjust the output of the hydrologic model. It is an open question if output-updating methods calibrated on simulated flow will still be valid for models forced with NWP model output. Furthermore, can output updating correct biases introduced by the NWP model (while also not conflicting with the bias adjustment mentioned in the previous recommendation)?

PERFORM HOLISTIC EVALUATION OF INTEGRATED FORECAST SYSTEM

As an experiment, the NWP model–based QPF resulting from the hydrologic system forced by advanced QPF can be input to the hydrologic model with post processing and bias adjustment to form an **integrated hydrologic forecast system**. The system should be used to hindcast streamflow in selected basins with various sizes and other characteristics. The results can be evaluated by comparing measured streamflow with simulations driven by atmospheric measurements and forecasts.

TEST METHODS FOR BLENDING ENSEMBLE FORECASTS ACROSS TIME SCALES

Many of the forecast centers and research studies used a single source of NWP model output. Usually, NWP model output is available at a variety of resolutions and lead times. The **integrated hydrologic forecasting system** should be forced with a seamless time series that includes the best information from all sources and is internally consistent. A few examples combine medium and seasonal forecasts such as Vitart et al. (2008), but it would be useful to know if these methods are relevant at short time scales.

5-3-2 Parameter Estimation and Predictive Uncertainty

It should be clear from the preceding chapters that limitations of both model structures and the data available on parameter values, initial conditions and boundary conditions, and methods of solution will generally make it difficult to apply a hydrological model (of whatever type) without some form of calibration (Conditioning). Moreover there are other errors (Uncertainties) such as:

- Uncertainties in the predicting of a calibrated model
- Uncertainties that have been overlooked such as **ambiguity concept** (Daliri, 2019 [3] and including know omissions and unknow unknowns [16].

In approaching the problem of model calibration or conditioning, there are a number of very basic points to keep in mind. These may be summarised as follows [16]:

-There is most unlikely to be one right answer. Many different models and parameter sets may give good fits to the data and it may be very difficult to decide whether one is better than another. In particular, having chosen a model structure, the optimum parameter set for one period of observations may not be the optimum set for another period. This is because so many of the sources of error in rainfall–runoff modelling are not simply statistical in nature (**aleatory uncertainties**). They are much more the result of a lack of knowledge (**epistemic uncertainties**, what Knight (1921) called the real uncertainties). In principle, epistemic uncertainties can be reduced by more observations and experiment. In practice, this tends to increase our appreciation of complexity without greatly improving predictions.

• Calibrated parameter values may be valid only inside the particular model structure used. It may not be appropriate to use those values on different models (even though the parameters may have the same name) or in different catchments.

• Model results will be much more sensitive to changes in the values of some parameters than to others. A basic **sensitivity analysis** should be carried out early on in a study. Different performance measures will usually give different results in terms of both the "optimum" values of parameters and the relative sensitivity of different parameters.

• Sensitivity may depend on the period of data used and, especially, on whether a particular component of the model is "**exercised**" in a particular period. If it is not, for example if an infiltration excess runoff production component is only used under extreme rainfalls, then the parameters associated with that component will appear insensitive.

• Model calibration has many of the features of a simple regression analysis, in that an optimum parameter set is one that, in some sense, minimises the overall error or residuals. There are still residuals, however, and this implies **uncertainty in the predictions** of a calibrated model. As in a statistical regression, these uncertainties will normally get larger as the model predicts the responses for more and more extreme conditions relative to the data used in calibration.

• Both model calibration (in the sense of finding an optimum parameter set) and model conditioning (finding a joint posterior parameter distributions) will depend on the shape of a **response surface** in the parameter space for the chosen performance or likelihood measure (Fig 5-14). The complexity of that surface depends on the interaction of the model with errors in the input data and, in some cases, on the implementation of the numerical solution to the model equations.

• Because of epistemic uncertainties, there can be no completely objective analysis of uncertainty in rainfall–runoff modelling. The analysis, therefore, depends on a set of assumptions that a modeller is

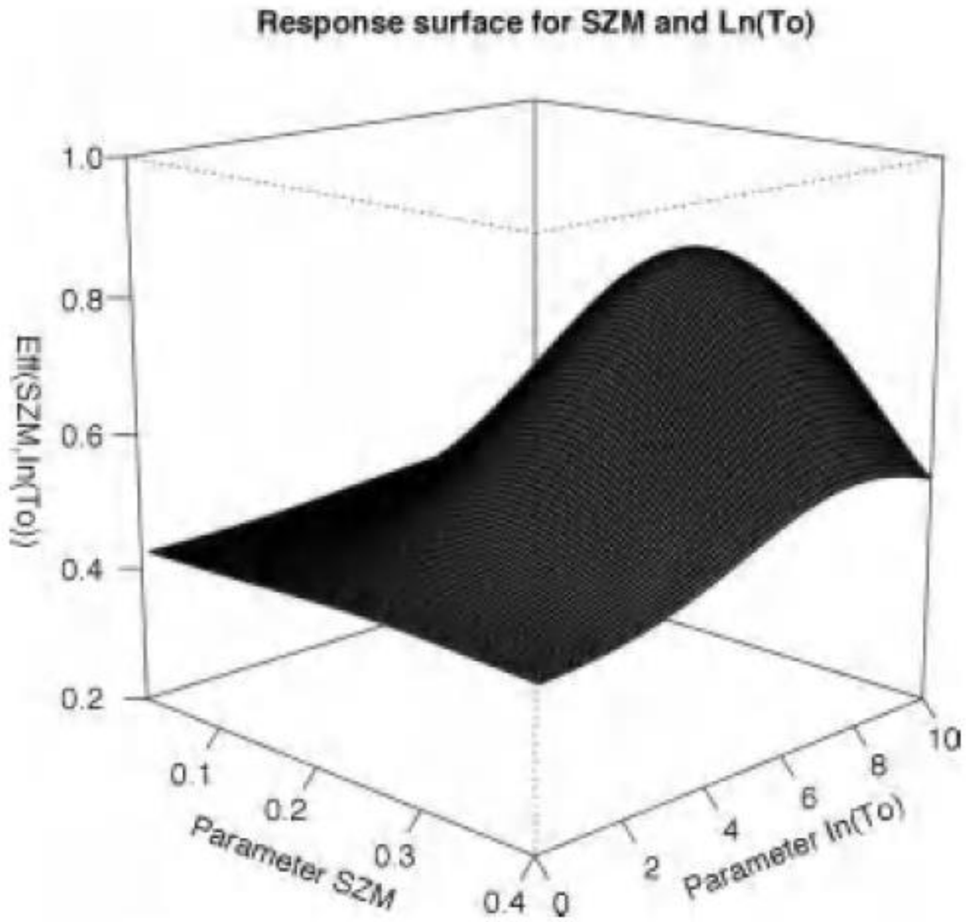

Figure 5-14 Response surface for two TOPMODEL parameters in an application to modelling the stream discharge of the small Slapton Wood catchment in Devon, UK; the objective function is the Nash–Sutcliffe efficiency that has a value of 1 for a perfect fit of the observed discharges[16]

prepared to accept and justify with a particular purpose in mind. Thus, the results of such an analysis should always be associated with a clear exposition of the assumptions on which it is based.

5-3-2-1 Methods of model calibrating

Methods of model calibration that assume an optimum parameter set and ignore the estimation of predictive uncertainty. These methods range from simple trial and error, with parameter values adjusted by the user, to the variety of automatic optimisation methods.

Sensitivity analysis and Performance measures

Once one or more models have been chosen for consideration in a project, it is necessary to address the problem of parameter calibration. It is unfortunate that it is not, in general, possible to estimate the parameters of models by either measurement or prior estimation. Studies that have attempted to do so have generally found that, even using an intensive series of measurements of parameter values, the results have not been entirely satisfactory (Beven et al., 1984; Refsgaard and Knudsen, 1996; Loague and Kyriakidis, 1997). Prior estimation of feasible ranges of parameters also often results in ranges of predictions that are wide and may still not encompass the measured responses all of the time (Parkin et al., 1996; Bathurst et al., 2004) [16].

The **efficiency** of parameter calibration would clearly be enhanced if it was possible to concentrate the effort on those parameters to which the model simulation results are most sensitive. This requires an approach to assessing parameter sensitivity within a complex model structure. Sensitivity can be assessed with respect to both **predicted variables** (such as peak discharges, discharge volume, water table levels, snowmelt rates, etc.) or with respect to some **performance measure**. Both can be thought of in terms of their respective response surfaces in the parameter space. One definition of the sensitivity of the model simulation results to a particular parameter is the local gradient of the response surface in the direction of the chosen parameter axis. This can be used to define a normalised sensitivity index of the form:

5-32
$$S_i = \frac{dQ/dx_i}{Q/x_i}$$

where Si is the sensitivity index with respect to parameter i with value xi and Q is the value of the variable or performance measure at that point in the parameter space (see, for example, McCuen, 1973)[16]. The gradient will be evaluated locally, given values of the other parameters, either analytically for simple models or numerically by a finite difference, i.e. by evaluating the change in Q as xi is changed by a small amount (say 1%). Thus, since the simulation results depend on all the parameters, the sensitivity Si for any particular parameter i will tend to vary through the parameter space (as illustrated by the changing gradients for the simple cases in Figure 5-14). Because of this, sensitivities are normally evaluated in the immediate region of a best estimate parameter set or an identified optimum parameter set after a model calibration exercise[3].

The definition of a **parameter response surface** as outlined above and shown in Figures 5-14 requires a quantitative measure of performance, goodness of fit or likelihood. It is not too difficult to define the requirements of a rainfall–runoff model in words: we want a model to predict the hydrograph peaks correctly, to predict the timing of the hydrograph peaks correctly, and to give a good representation of the form of the recession curve to set up the initial conditions prior to the next event. We may also require that, over a long simulation period, the relative magnitudes of the different elements of the water balance should be predicted accurately. The requirements might be somewhat different for different projects, so there may not be any universal measure of performance that will serve all purposes Fig 5-15).

Automatic optimisation methods

Detail discussion of these techniques in respect of hydrological models is given by Sorooshian and Gupta (1995). Main methods we can mention shuch as Hill-climbing, Simulated Annealing and Genetic algorithm (GA) [16].

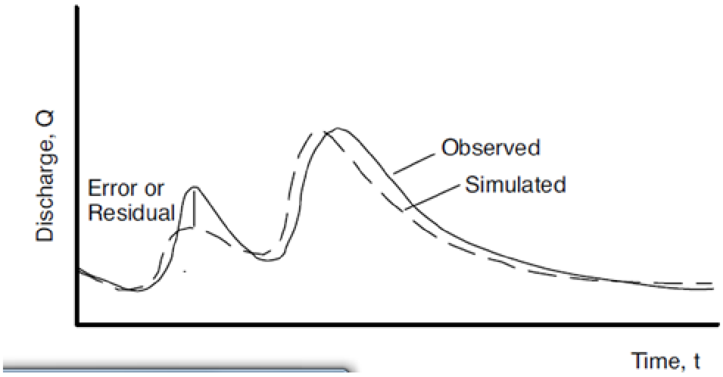

Fig. 5-15 Comparing observed and simulated hydrographs

Hill-climbing techniques for parameter calibration have been an important area of research since the start of computer modelling in the 1960s. Hill climbing from any point on the response surface requires knowledge of the gradient of that surface so that the algorithm knows in which **direction to climb**. The available techniques may be classified into two basic types. **Gradient algorithms** require the gradient of the response surface to be defined analytically for every point in the parameter space. Mathematically, this requires that an analytical expression be available for the differential of the model output with respect to each parameter value. These methods are not generally used with hydrological models since it is often impossible to define such differentials analytically for complex model structures. Much more commonly used are “**direct search**” algorithms that search along trial directions from the current point with the aim of finding improved objective function values. Different algorithms vary in the search strategies used. Algorithms that have been widely used in rainfall–runoff modelling include the **Rosenbrock (1960) method** and the **Simplex method** (Nelder and Mead, 1965). The latter is explained in a hydrological context by Sorooshian and Gupta (1995) and Daliri. 2009,[3][19][20].

Recognising kind of uncertainty in models and data (Analysis)

Recognising uncertainty in models and data is vital task for **hydrologists**. Methods of uncertainty estimation that are based only on prior assumptions about different sources of uncertainty. These methods are grouped under the name “forward uncertainty analysis”.

In this section, we consider only cases where no observations are available for constraining uncertainty through a calibration or conditioning process. In that case, uncertainty estimation has to depend on prior assumptions about the different sources of uncertainty. This is then a “forward uncertainty estimation” exercise. In most practical applications, it involves an analysis conditional on the choice of a certain model structure. We do not try to evaluate the effects of uncertainties that have been knowingly or unknowingly overlooked.We are therefore left with the uncertainties in the initial and boundary conditions and uncertainties in the parameter estimates. To carry out a forward uncertainty estimation we need to decide on the nature of those uncertainties and how they might be represented (for example, as statistical distributions or fuzzy variables or …).

Once those decisions are made, the uncertainties must be propagated through the model. In the unusual case of a model that is linear in its responses and parameters, this can be done analytically (see, for example, Beven, 2009)[16]. Rainfall−runoff models (with the exception of simple linear transfer functions for runoff routing) are nonlinear, so it is more usual to propagate the uncertainty using a **Monte Carlo sampling** technique. This involves taking random samples from the specified distributions, taking account of any interactions if they have been specified as joint distributions, and running the model with the chosen values. If the distributions are sampled according to the probability density of the specified distributions (for example, using the **Latin Hypercube** technique of Iman and Conover (1982) then this can be a relatively efficient process even for a large number of uncertain variables. More approximate methods (for example, those reviewed by Melching, 1995[16]) were valuable when computer power was much more limited but have now almost completely disappeared from use. The output from such a Monte Carlo study is a set of model "realisations", each of which is associated with a probability (equal if the samples have been drawn to reflect the probabilities defined by the prior distributions) and a set of output variables. Thus the distributions of the output variables can be formed and different types of uncertainty intervals extracted.

The aim of uncertainty estimation is to assess the probability of a **certain quantity**, such as the peak discharge of an event, being within a **certain interval** but it is worth noting that different types of interval might be required. Hahn and Meeker (1991), for example, distinguish three different types of interval[16]:

A confidence interval contains the estimate of an unknown characteristic of the quantity of interest, for example the mean peak discharge of the event. Since we cannot estimate the peak discharge precisely from the sample of model runs available, even the estimate of the mean is uncertain. The confidence interval can be used to define the mean estimate with specified probability. Most often, 5% and 95% limits are used to define a confidence interval (i.e. a 90% probability that the value lies within the interval). Confidence limits can also be calculated for other summary quantities for the distribution of peak discharge, such as the variance or even a quantile value.

• A tolerance interval is defined so as to contain a certain proportion of the uncertain model estimates of an observation used in model calibration. For the peak discharge example, tolerance intervals could be defined for the model predictions of a particular observed peak used in model calibration.

• A prediction interval can be defined as the interval containing a certain proportion of the uncertain model estimates of peak discharge (or any other predicted variable) for a future event. In rainfall−runoff modelling, we are mostly interested in prediction intervals after calibration or conditioning of a model. Uncertainty limits are related to the changes in the predicted variable in the parameter space or, more precisely, if a predicted variable (rather than the performance measure) is represented as a surface in the parameter space, to the gradient or slope of the surface with respect to changes in the different parameter values. If the slope is steep then the uncertainty in the predictions is large. If the slope is quite small, however, then the uncertainty is predicted as small since the predicted variable changes little if the parameter is considered to be uncertain. Recalling Equation (5-32), the slopes are an indication of the local sensitivity of the predictions to errors in the estimation of the parameter values.

5-3-2-2 Considering predictive uncertainty

There are some methods for model calibration to consider some above uncertainties such as **Bayesian** statistical methods, **Theoretic** methods and **GLUE** method (Generalised Likelihood Uncertainty Estimation) [16].

For example, More recently, however, Bayesian methods have come to dominate statistical analysis again, primarily as a result of the more sophisticated and powerful computer methods that can be brought to bear in estimating the posterior distribution and resulting **prediction uncertainties** for nonlinear models.

Bayesian analysis requires three basic elements:

• a definition of the prior distribution for the uncertain quantities to be considered (in some cases," noninformative" priors might be defined where there is no prior knowledge about a quantity);

• a definition of the likelihood function that reflects how well a model can predict the available observations;

• a method for integrating the product of prior probabilities and likelihoods to calculate the posterior distribution

We can also use several models with parameters sets to product a range of variable distribution probability based on experience of the hydrologist to consider total uncertainties, Daliri, 2019 [3]. An alternative approach to model calibration is to try to determine a set of acceptable models. Set theoretic methods of calibration are generally based on Monte Carlo simulation. A large number of runs of the model are made with different randomly chosen parameter sets. Those that meet some performance criterion or criteria are retained, those that do not are rejected. The result is a set of acceptable models, rather than a single optimum model. Using all the acceptable models for prediction results in a range of predictions for each variable of interest, allowing an estimation of prediction intervals. This type of method has not been used widely in rainfall–runoff modelling (with the exception of the GLUE variant described in follow) but there were a number of studies in water quality modelling (see, for example Klepper et al., 1991; Rose et al., 1991; van Straten and Keesman, 1991). To demonstrate the use of the model and the resulting prediction limits with the Sacramento ESMA type rainfall–runoff model, researchers used in the US National Weather Service River Forecasting System, in an application to the Leaf River catchment, Mississippi. The model has 13 parameters to be calibrated. Two performance measures were used in the calibration, a sum of **squared errors** and a **heteroscedastic maximum likelihood criterion**. 500 parameter sets were evolved to find the Pareto optimal set, requiring 68 890 runs of the model. The results are shown in terms of the grouping of the 500 final parameter sets on the plane of the two performance measures (from Yapo et al., 1998) and the associated ranges of discharges predicted by the original randomly chosen parameter sets and the final Pareto optimal set (from Gupta et al., 1998). A major advantage of the Pareto optimal set methodology is that it does not require different performance measures to be combined into one overall measure.

Gupta et al. (1999) suggest that this method is now competitive with interactive methods carried out by a modelling expert in achieving a calibration that satisfies the competing requirements on the model in fitting the data.

If we accept that there is no single correct or optimal model, then another approach to estimating prediction limits is to estimate the degree of belief we can associate with different models and parameter sets: this is the basic idea that follows from **recognising the equifinality** of models and parameter sets (Beven, 1993, 2006a, 2009)[16]. Certainly we will be able to give different degrees of belief to different models or parameter sets, and many we may be able to reject because they clearly do not give the right sort of response for an application. The "optimum", given some data for calibration, will have the highest degree of belief associated with it but, as we discuss in this section, there may be many other models that are almost as good. In the GLUE methodology, a prior distribution of parameter values is used to generate random parameter sets for use in each model using Monte Carlo simulation. An input sequence is used to drive each model and the results are compared with the available calibration data. A quantitative measure of performance is used to assess the acceptability of each model based on the modelling residuals. Any of the appropriate likelihood measures could serve this purpose. The only requirements are that the measure should increase monotonically with increasing goodness of fit and that "nonbehavioural" models should have a likelihood of zero. Different likelihood measures or combinations of likelihood measures will, however, lead to different estimates of the predictive uncertainty. In using the model for predictions, all simulations with a likelihood measure greater than zero are allowed to contribute to the distribution of predictions. The predictions of each simulation are weighted by the likelihood measure associated with that simulation. The cumulative likelihood weighted distribution of predictions can then be used to estimate quantiles for the predictions at any time step.

Implementation of the GLUE methodology requires a number of decisions to be made as follows:

- which model or models to include in the analysis;
- a feasible range for each parameter value;
- a sampling strategy for the parameter sets;
- an appropriate likelihood measure or measures, including conditions for rejecting models that would not be considered useful in prediction on the basis of their past performance, so leaving those that are considered behavioural.

These decisions are all, to some extent, subjective but an important point is that they must be made explicit in any application. Then the analysis can be reproduced, if necessary, and the decisions can be discussed and evaluated by others.

Dynamic Parameters and Model Structural Error

In particular, the potential interaction between input errors and model structural errors was noted (see also Beven, 2005). **Model structural error** in statistical analysis of uncertainties is generally ignored (unless some identifiable functional form of model inadequacy or discrepancy function can be defined;

model identification is generally carried out as if the model was correct. But of course, in hydrology, we know very well that the model is only a very approximate representation of the complexity of the processes occuring in a catchment, and in some cases might not be at all good. Thus, assuming the model is correct might not be a good assumption. Application of several model sets may be useful for this challenge. So, As noted earlier, multiple model structures are easily incorporated into the equifinality principle and the GLUE framework, as long as each model structure is subject to the same type of evaluation to infer a likelihood weighting. Another approach has been to use filtered estimates of parameter distributions that are allowed to evolve over time (dynamic identifiability (DYNIA) approach ofWagener et al. (2003) [16].

Some sources of GLUE software are listed here:

A more detailed guide to software for random number generation and uncertainty estimation methods can be found at www.uncertain-future.org.uk.

GLUE Lancaster University provides a Windows (32 bit only) demonstration GLUE package as a teaching aid. It provides tools for sensitivity analysis and uncertainty estimation using the results of Monte Carlo simulations. It is available from www.lec.lancs.ac.uk/research/catchment and aquatic processes/software.php.

A MATLAB version of GLUE has been developed by Marco Ratto at the EU Joint Research Centre, Ispra, Italy. This allows for more parameters and more Monte Carlo runs than theWindows demonstration version and can be downloaded from http://eemc.jrc.ec.europa.eu/Software-GLUEWIN.htm.

DYNIA, with GLUE, is included in the Imperial College Monte Carlo toolbox for MATLAB that can be found at www3.imperial.ac.uk/ewre/research/software/toolkit.

PEST is a suite of software for parameter estimation, sensitivity analysis and uncertainty estimation, developed by John Doherty *et al.* It is applicable to a wide range of models including highly parameterised distributed models. It has a variety of regularisation techniques to reduce the parameter dimensions. The main inversion technique is based on a weighted least squares approach. It is available from www.pesthomepage.org/Home.php.

UncertML OGC-compatible standards for communicating uncertainty in variables and model results are being developed under the UncertML project. See www.uncertml.org.

5-3-3 Decision making under uncertainty and Risk

We can use of those uncertain predictions?

One interpretation is in terms of the risk of a certain outcome in certain circumstances, given the model as a means of extrapolating knowledge and understanding to those circumstances. Both statistical and nonstatistical approaches to uncertainty estimation can be interpreted in this way. In essence, evaluating the risk of an outcome based on the model predictions is also an evaluation of the risk of the model predictions being wrong (as they may well prove to be).

Risk, however, is something that is readily incorporated into modern decision-making processes, when it may also be necessary to take account of the costs of mitigating that risk, for example, in enlarging a reservoir spillway or raising flood embankments (section 5-3-3-1 & 5-3-3-3). The important point is that the risk associated with the model predictions should be included in the decision analysis. In risk-based decision making, a common technical definition of risk is as:

Risk = *probability* * *consequences*

In the general case, both the probability and the consequences should be considered as uncertain quantities themselves. The consequences are usually some expected loss (often expressed in monetary terms). Such uncertainties might affect the decision that is made about reducing the risk, so it is important that they be incorporated into the analysis.

One rather simple way of doing so is to integrate over all the uncertainties to produce a cumulative distribution (**pcd**) of risk. This can then (as in the simple case of estimating a flood frequency) be expressed in terms of the exceedance probability (EP) of a given level of loss. Thus, the $EP(x > X)$ can be defined in terms of the cumulative density function of the risk of an outcome $F(X)$, obtained by integrating over all probabilities of a consequence less than X, given the probabilities of possible outcomes (both of which might involve some uncertainty): $(EP(x > X) = 1 - F(X))$.

There are many example about risk nanlysis in water supply and river hydrauilic calculations in text of [3].

5-3-3-1 Short-term future risk management: Flood Forecasting

Catchment (river basin or watershed, urban area) systems are not stationary systems; both their characteristics (time of concentration, land use, soil infiltration, slop, climate, debt regime, drainage, water table, soil moisture, effective area, …) and the inputs (ran intensity and movement, duration, ..) which drive the hydrology are changing over time and space (Milly et al., 2008). There are two types of future risk that need to be managed in catchment hydrology where rainfall−runoff models can play a useful role. The first is the short-term forecasting problem of whether an important flood discharge with the potential to pose a threat to life or property will occur. The second is the longer term seasonal or decadal prediction problem of whether changes in catchment characteristics or climate might pose a threat to water resources or flood and drought frequencies. Both of these problems are dependent on the inputs from weather and climate prediction models, which are associated with significant uncertainties in their predictions, including **epistemic uncertainties**. Managing these risks therefore requires consideration of a cascade of uncertainties through multiple model components and seeking ways to constrain the resulting uncertainty using forms of data assimilation wherever possible (e.g. Pappenberger et al., 2005b).

Predicting the longer term hydrological effects of change of both climate and land use is certainly a currently fashionable indoor sport but can effect to flood characteristics by the impacts of global warming, deforestation and other changes such as the greenhouse effect, the ozone hole over Antarctica, the El Ni˜no effect, satellite pictures of burned and burning forests in Amazonia and the increasing demands of a growing global population on the world's freshwater resources and land. Hydrological modelling contributes only a small part of the Global Atmosphere−Ocean−Land Modelling systems that are being used to predict changes into the next century. It is not, however, an insignificant part. Global circulation models (**GCMs**) are known to be sensitive to how the hydrology of the land surface is represented.

It follows that, as with models of present-day hydrological responses, we should be qualifying our predictions by estimating uncertainties of the impacts of change or, put in another way, the risk of seeing a certain degree of impact on flood peaks, minimum flows or the usable water resource in the future. Translating uncertainty into a future risk can provide a valuable contribution to the **decision-making** process. Risk is the more acceptable face of uncertainty. The decision maker is then faced, rather than a prediction surrounded by a fuzzy cloud of uncertainty, with the more manageable problem of assessing an acceptable risk. The information provided by the simulations is essentially the same.

Managing risk in the short term is one of the most important applications of rainfall−runoff modelling, particularly for flood forecasting which requires decisions to be made as to whether flood warnings should be issued on the basis of the data coming in from raingauges, radar rainfall images, stream gauges and the model predictions as the event happens in "**real time**". This is a risk management problem because of the uncertainties inherent in the modelling process. It is a case where taking account of the uncertainties might make a difference to the decision that is made (Krzysztofowicz, 2001a; Todini, 2004).

There are a number of simple principles for real-time operational forecasting that can be expressed as follows[16]:

- The event of greatest interest is the next event when a warning might (or might not) need to be issued.
- The next event is likely to be different from all previous events in some of the details of rainfall pattern, volumes and observation uncertainty; rainfall forecast uncertainty; antecedent condition and runoff generation uncertainty; and rating curve uncertainty where discharges for overbank flows are of interest.
- Allowing for uncertainty means being right more often in terms of bracketing when warning thresholds are crossed. It also gives a more realistic representation of forecasting capability in communicating with professional partners.
- Estimating the uncertainty associated with any forecast should not be the end point of the analysis. There are still issues about communicating the assumptions of the analysis to those who have to act on predictions, of managing uncertainty by post-event analysis, and of trying to reduce the uncertainty by more effective measurements (and longer term improvements in the underlying science).

The requirement is for the forecasts and warnings for an area at risk of flooding to be made as **accurately** as possible and as far ahead as possible or with the greatest possible **lead time**. We can use a model for these predictions that has been calibrated on historical data sets but, because every event has its own peculiarities, we should expect that during a flood event the model predictions of river stage or discharge will start to deviate from those values being received online at a flood forecasting office from the telemetry outstations. Thus, in any flood forecasting situation it is useful to have data assimilation methods that both allow for **real-time updating** of the forecasts as the event proceeds and constrain the uncertainty in the forecasts. This is particularly the case where the sources of uncertainty are not simply random but can be the result of lack of knowledge. Krzysztofowicz (2002), for example, suggests that:

> operational uncertainty is caused by erroneous or missing data, human processing errors, unpredictable interventions (e.g. changes in reservoir releases not communicated by a dam operator to the forecaster), unpredictable obstacles within a river channel (e.g. ice jams, trash under bridge,..), and the like.

To these we might add the potential for unexpected breaches of flood defences during an event. In forecasting (rather than simulation), these sources of epistemic uncertainty can be at least partially compensated by the use of **adaptive modelling methods**.

Forecasting methods based on transfer function modelling are ideally suited to these requirements and have been quite widely implemented (see, for example, SempereTorres et al., 1992; Cluckie, 1993; Moore et al., 1990; Lees et al., 1994; Young, 2002; Romanowicz et al., 2006, 2008). An example application using the DBM (data-based mechanistic) methodology is provided by Leedal et al. (2008), who describe the implementation of a flood forecasting system for the town of Carlisle on the River Eden in Cumbria, the model **assimilates data** at each gauging station site and generates forecasts with a six-hour lead time.[16].

5-3-3-2 Rainfall-Runoff modeling for FF

Data requirements

One of the most important ways of mitigating the costs of flood damage is the provision of adequate warnings, allowing people to act to protect their property and themselves. This process is very much easier in large catchments where the build up of a flood and the transmission of the flood wave downstream can take days or even weeks. In small catchments, with short times to peak, real-time flood forecasting, is much more difficult. The most extreme discharges in such catchments tend to occur as a result of localised convective rainfalls or high intensity cells within larger synoptic weather systems.

Events where the required lead time for issuing a warning is less than the catchment response time are called “**flash floods**”. The potential for a flood-producing rainfall might be recognised but it may be very difficult to specify exactly where. To make adequate warnings requires knowledge of the rainfalls as they occur or, even better, accurate forecasts of potential rainfall intensities **ahead of time**, which would allow an increase in the forecast lead time that might be important for small catchments and flash floods.

Forecasting rainfalls generally now involves a combination of projecting **radar rainfall images** into the future and **ensemble weather predictions** of future precipitation (for example the UK Met Office NIMROD radar and MOGREPS forecast products).

At least for cases where the catchment response time is greater than the lead time for decision making, this makes it important that any rainfall–runoff model used be capable of real-time adaptation to take account of any errors in the forecasts resulting either from errors in the inputs, whether from radar or rainfall, or from error in the model structure. This requires, however, that the flood warning centre also receive information about river stages in real time, at one or more gauging stations in a catchment, so that model forecasts can be compared with observed stages or discharges in real time and the model adapted to produce more accurate forecasts (at least until the gauge is washed away or the telemetering system fails).

There is another reason why observed stage information might be useful in flood warning, particularly in larger catchments where the time delays in the channel system are sufficiently long compared with the required lead time for a forecast. In general, **two to six hours** would be the minimum feasible lead time to allow a warning to be transmitted to the public but longer lead times might be needed for decisions about deploying demountable flood defences, for example. A measurement of the discharge or stage upstream can be used as part of the system for forecasting the stage and discharge and timing of the flood peak further downstream. Such observations can also help constrain the uncertainty in propagating forecasts from the headwaters of a catchment in predicting the risk to flood-prone areas downstream.

In general, flood warnings are issued in relation to the forecast stage of the river at a critical gauging point without modelling the detailed pattern of inundation upstream of that point. In many situations this may be adequate, since if flooding is predicted to occur somewhere in the flood plain, then a **general warning** can be issued. In large rivers, however, such as the Mississippi, the progress of the flood wave downstream may be very much controlled by the pattern of inundation during the flood, including the effects of dyke failures which are inherently difficult to predict ahead of time. Thus it may be necessary to use a hydraulic routing model in forecasting the expected depths downstream, continually revising the calculations as conditions change (although transfer function methods can also be used for this purpose for specific sites; see, for example, the work of Beven et al. (2008), which includes the use of **data assimilation** where measured levels are available. The use of a hydraulic model adds the requirement of knowing the channel and flood plain topography, together with parameters such as effective resistance coefficients. Channel form, can of course change during a flood event due to erosion and deposition. Models of sediment transport in rivers have not advanced to the stage where they can be used operationally and most current hydraulic flood routing models use a "**fixed bed**" assumption.

rainfall–runoff modelling

Any rainfall–runoff model that has been calibrated for a particular catchment can be used in the prediction of flood discharges[16]. The US National Weather Service River Forecast System (Burnash, 1995), for example, is a development of the Sacramento model, a form of lumped explicit soil moisture accounting model with many parameters to be calibrated (see, for example, Sorooshian et al., 1992; and Gupta et al.,1999).

Experience suggests that uncertainty in both measurements and predictions of flood peaks increases with peak magnitudes. In addition, even if a model has been calibrated for a certain range of discharges, uncertainty is bound to increase as predictions are made outside this calibration range for extreme events. Thus, it may not be possible to predict ahead of time whether a flood stage will definitely be exceeded in a event; it may, however, be possible to assess **the risk that the flood stage** will exceeded by consideration of the distribution of (uncertain) predictions.

An early comparison of real-time forecasting methods, including adaptive schemes, was carried out by the World Meteorological Organisation (**WMO**, 1975) and a review of approaches has been given by Moore (1999). **Ensemble forecasting systems** have been reviewed by Cloke and Pappenberger (2009) including experience from the Hydrological Ensemble Prediction Experiment (**HEPEX**) (Schaake et al., 2007).

It is also possible to take an approach that makes no attempt at all to model runoff generation during flood forecasting. As noted in before chapters, **neural net models** and support **vector machine models** have been popular as a means of estimating N-step ahead flood discharges, using inputs that include rainfalls and previous values of discharge or water levels and a training set of historical events. In discussing neural network models, however, it has already been noted that such models are grossly over-parameterised and there has to be some concern then that methods based only on data analysis might not be accurate in predicting events more extreme than those included in the training set.

The Lambert ISO model

The first model is an **adaptive deterministic method** due to Lambert (1972) that is very difficult to beat in forecasting the response of small catchments. This Input−Storage−Output (**ISO**) model has been used in a number of UK flood forecasting schemes, particularly in the River Dee catchment in north Wales.

Adaptive Transfer Function models for real time forecasting

As noted earlier, the propensity for error in the predictions during extreme events also suggests that it would be advantageous to use an **adaptive modelling strategy**, so that if a comparison of observed and predicted discharges reveals that the model predictions are in error, then a strategy for adjusting the model predictions can be implemented. This is clearly only possible where discharge or river stage measurements can be made available in real time. Adaptation is also more easily implemented for simpler models. Adaptive transfer functions can be used for both rainfall−runoff and upstream discharge (or stage) to downstream discharge (or stage), depending on what data are available. The example application presented in the case study is for an operational forecasting model for the town of Carlisle in Cumbria, that uses both rainfall−flow and discharge−discharge transfer functions. Adaptation of such models can be implemented in a number of different ways. In the Carlisle model, a simple adaptive gain parameter is used, i.e. the transfer function is scaled up or down in real time without changing its form. This simple approach has proven very effective in this and other applications.

The Bayesian forecasting system (BFS) and Quantile regression
The Bayesian forecasting system and quantile regressions as other ways of adding uncertainty to the forecasts of deterministic rainfall–runoff models [16].

software

These types of model can be made part of a larger flood forecasting system that includes flood routing components. For the River Dee catchment, for example, ISO models were developed for all the gauged subcatchments and linked to a flood routing model. The Forecasting and EarlyWarning System (FEWS) developed by Deltares in the Netherlands (e.g. Werner *et al.*, 2004) provides a unified framework for networking different model components in this way that has been implemented in a number of other countries including the UK Environment Agency National Flood Forecasting System. The FEWS software is freely available under licence.

5-3-3-3 Optimal Design of Levee, Dam and Flood Control Systems
Optimal design to operating policy of hydraulic structures's single flood control system (dyke, dam reservoirs) or multiple systems (water supply and flood control dams) can based on flood forecasting systems and risk-based concepts[3].
Upstream flood reservoir operations and downstream levee construction are two common ways to protect from flooding. Most traditional risk-based analyses for optimal levee design focus primarily on **overtopping failure**, and few risk analysis studies explicitly include the more frequently observed **intermediate geotechnical failures**. So, we can first develops a risk based optimization model and for single levee designs given two simplified levee failure modes[22]:

- overtopping and
- overall intermediate geotechnical failures.

The optimization minimizes the annual expected total cost, which sums the expected annual damage cost and annualized construction cost. This optimization model is then extended to examine a common simple levee system with levees on opposite river banks, allowing flood risk transfer across the river. The economic optimality of asymmetric levee system is demonstrated mathematically and analytically, for overtopping failure, overall intermediate geotechnical failure and a **combination of failure modes**. Where residual flood risk is completely transferred to the low-valued river bank at economic optimality, individuals may be compensated for the transferred flood risk to guarantee and improve outcomes for all parties. Such collaborative designs of the two levee system are economically optimal for the whole system. However, rational and self-interested land owners that control levees on each river bank separately often tend to independently optimize their levees. By applying game theory to the simple levee system, the cooperative game with a system-wide economically optimal design and the single-shot non-cooperative Nash equilibrium are identified, and the successive repeated non-cooperative reversible and irreversible games are examined. Compensation for the transferred flood risk can be determined by comparing different types of games and implemented with land owners' agreements on allocations of flood risk and benefits. The resulting optimized flood risks to a downstream leveed area would further affect the upstream reservoir's operation in optimizing flood hedging prereleases, which would create a small flood downstream by pre-storm release to reduce the likelihood of a larger more damaging flood in the future. Overall damages from flood pre-release decisions must be convex for flood hedging to be optimal. Some theoretical conditions for optimal flood hedging are explored: the fundamental one is that the current marginal damages from pre-releases equals the future marginal expected damages from storm releases. Any additional economic water supply lost from pre-releases tends to reduce the use of hedging prerelease for flood management[22].

5-3-3-4 FF Using Machine learning methods

Nowadays, the degree and scale of flood hazards has been massively increasing as a result of the changing climate, and large-scale floods jeopardize lives and properties, causing great economic losses, in the inundation-prone areas of the world. Early flood warning systems are promising countermeasures against flood hazards and losses. A collaborative assessment according to multiple disciplines, comprising hydrology, remote sensing, and meteorology, of the magnitude and impacts of flood hazards on inundation areas significantly contributes to model the integrity and precision of flood forecasting. Methodologically oriented countermeasures against flood hazards may involve the forecasting of reservoir inflows, river flows, tropical cyclone tracks, and flooding at different lead times and/or scales. Analyses of impacts, risks, uncertainty, resilience, and scenarios coupled with policy-oriented suggestions will give information for flood hazard mitigation. Emerging advances in computing technologies coupled with big-data mining have boosted data-driven applications, among which Machine Learning technology, with its flexibility and scalability in pattern extraction, has modernized not only scientific thinking but also predictive applications. Readers can explores recent Machine Learning advances in flood forecast and management in a timely manner and presents interdisciplinary approaches to modelling the complexity of flood hazards-related issues, with contributions to integrative solutions from a local, regional, or global perspective for example: **Building an Intelligent Hydroinformatics Integration Platform for Regional Flood Inundation Warning Systems and ect** (Fig 5.16).

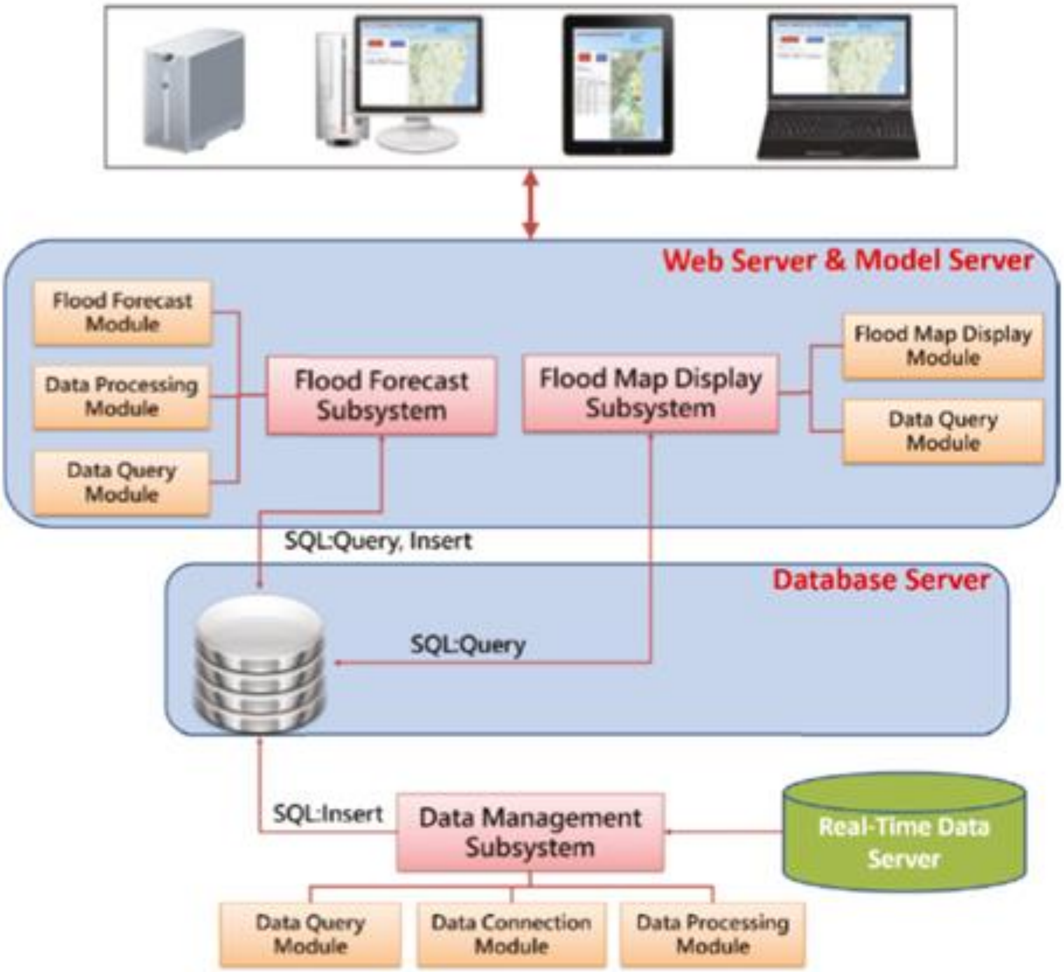

Figure 5-16. Relationships between four servers, five modules and three sub-systems [22]

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UNCERTAINTIES,
IN FLOOD FORECASTING SYSTEMS MODELLING

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FFWS

Flood Forecasting Systems (**FFS**) and warning systems (**WS**) forms an important tool in reducing vulnerabilities and flood risk and form an important ingredient of the strategy to "live with floods", thereby contributing to **national sustainable development.**

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