FLOOD EVALUATION, HAZARD DETERMINATION AND RISK MANAGEMENT

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FOREWORD

Design criteria for the construction or rehabilitation of dams and appurtenant structures generally starts with a section defining the design flood. Methods for determining flood design have evolved over the years, but these must continue to progress given the degree of uncertainty in the assessment of extreme floods and the fact that factors external to floods must be considered in the risk assessment.

Five bulletins have been published by the Flood Evaluation and Dam Safety Committee since its formation:

- Project Flood Selection - Current Methods (No 82, 1992);
- Dams and Floods - Guidelines and Case Studies (No. 125, 2003);
- Role of Dams in Flood Prevention - Summary (No. 131, 2006);
- Integrated Flood Management (No. 156, 2010);
- Flood Assessment and Dam Safety (No. 170, 2018).

This bulletin follows the lead of the previous bulletin. It discusses issues of concern to committee members and we hope it will allow users to better understand some of the challenges ahead, approaches to solve problem encountered in this field of expertise and future trends.

It consists of three main chapters following the introductory chapter. Chapter Two discusses the main aspects related to the volume of floods. In general, a flood is often associated with the consequences due to its the peak flow. However the volume of floods is also an important aspect to consider.

Chapter Three is a follow-up to the previous bulletin, addressing in more detail the stochastic approaches to flood risk assessment. These analyses include factors that are independent of flood but may have an impact on the safety of the dam(s) in the system under study.

Finally, the last chapter deals with the forecast aspects related to the proactive management of floods. Case studies to illustrate short-, medium- or long-term management challenges are presented in Appendix A of this document.

Il It should be mentioned that all members of the committee participated in one way or another in the design of the chapters of this bulletin (work done mostly on a voluntary basis). I thank them personally.

I must highlight the contribution of the main authors of each chapter. By sharing their expertise and enthusiasm to work in this area, their work has become the core of this bulletin. Those are :

-	Chapter 2	Bernard Joos	Switzerland
		Luis Berga	Spain
-	Chapter 3	Zoran Micovic	Canada
-	Chapter 4	Uwe Muller	Germany
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1. INTRODUCTION

EXTREME FLOODS AND THEIR CONSEQUENCES

As part of the hydrological studies required to assess and/or ensure the safety of dams, dikes and hydraulic structures, we spend a lot of time evaluating the characteristics of floods and more particularly peak inflows in the system.

It should be remembered that the primary purpose of dam safety studies is rather to evaluate the potential consequences when the dam and other components of the system are confronted with extreme events and that does not only depend on the peak discharge during major floods.

Knowledge of the system as well as the parameters that may impact the security of its components is essential. For example, the routing capacity of the system (run-of-river, daily, seasonal, annual, or multi-year reservoir) plays a role in the system's ability to respond to major floods. A small reservoir (small in comparison to its inflows) will be more sensitive to the peak discharge during a major flood than the flood volume; the time to react to such event could be relatively short. A large reservoir will normally be more sensitive to the flood volume, depending on its routing capacity. This will allow more time to react to the flood, however the consequences related to a failure could be much more important.

Other factors must also be considered, factors that will be more or less homogeneous and that will depend, in part, on characteristics not controlled by the dam owners. We will mention here the initial conditions on the watershed, the temporal distribution and intensity of the precipitation on the basin, the snow cover and the temperature of the air (if applicable), the vegetation and the rate of urbanization, ...

As previously mentioned, knowledge of the system under study is therefore a critical factor in assessing the consequences of extreme events and determining the best way to respond to these events. To do this, the system must be well documented while considering that the situation will continue to evolve over time and the main trends must be identified.

If the knowledge of the system is essential, we often have to face limitations resources, time and knowledge available to perform the analysis.

Not having the same resources or knowledge of a system does not mean that we must accept more risk, but rather it could mean that we have to be more conservative in the design or the maintenance of the system, which also have an impact.

If we have resources and time required to perform more detailed analyses, we still have to ask ourselves a few questions :

- Is our knowledge of the different variables having an impact on dam safety sufficient to establish a realistic distribution? What are the correlations between a parameter and the other parameters?

- If we are evaluating various scenarios for a parameter (let's consider parameters related to climate changes), are all scenarios equiprobable?

We know that we will not be able to consider all the combinations causing a failure of the system, however are we realistic in our risk estimates for the scenario identified ?

Aristotle stated that « the true and the approximately true are apprehended by the same faculty; it may also be noted that men have a sufficient natural instinct for what is true, and usually do arrive at the truth. Hence the man who makes a good guess at truth is likely to make a good guess at probabilities. »

However, to ensure the safety of a dam, a good instinct is not enough and understanding of all the components and risks to the system is essential.

THE BULLETIN

This bulletin is divided in three main chapters.

Chapter 2 focuses on an aspect of floods that is often more important for large reservoirs, i.e. flood volume. For small reservoirs with low regulation capabilities, peak flow is the most important feature, as the reservoir can not have a significant impact on outflow. On the other hand, for larger reservoirs, an adequate assessment of the flood volume and its relation to the peak flow is essential. This chapter reviews some aspects related to flood volumes and provides a specific point of view on some approaches or perceptions, for example:

- The effect of the temporal distribution of the precipitation over the peak discharge and the flood volume is not always as important as is commonly believed over the peak discharge and the flood volume;

- The recession phase of a flood on a watershed depends on the physical characteristics of the basin and the pattern does not depend on the size of the flood;

- It is possible to build a hydrograph caused by two distinct events by knowing the characteristics of the flood on a watershed;

- It is often common practice to consider that the peak discharge of a major flood and the flood volume have a similar recurrence period. This may be true for floods caused by a single event, but it seems to be less so for floods caused by a combination of events.

- The large floods observed around the world can serve for comparison purpose to validate or predict the characteristics of large floods on other watersheds.

Chapter Three is a follow-up to our previous technical bulletin (No 170), reviewing the current trends in the evaluation of extreme flood. While the previous bulletin reviewed possible approaches with a particular focus on stochastic approaches, this bulletin focuses exclusively on stochastic approaches, describing in more detail the different phases of such studies.

Stochastic approaches do not focus only on uncertainties related to floods and their characteristics (peak, volume, hydrograph), but rather on the consequences following extreme floods, i.e. in this context at the level reached in the reservoirs and the consequential risks for the various components of the system.

Validation of the results is also discussed in the chapter. Although it is difficult to validate the results obtained for extreme floods (given the low probability of these events), it is easier to validate the proposed approach for floods of more common periods of recurrence. Aspects related to sensitivity analyses and uncertainties are also addressed. The uncertainties associated with stochastic studies will be addressed specifically in the next bulletin.

The final chapter addresses the challenge of proactive flood forecasting to minimize potential consequences and damage. The chapter is more focused on the operation of existing systems, so it is more for operators who are looking to improve the management of their systems.

This chapter introduces first the basics and fundamentals of proactive flood management. Then the different horizons of analysis are considered, either short, medium or long term. Different approaches are then discussed, i.e. by moving from analyzes based on the observed history (long term), to the forecast of a single event (short term). In addition, there is nothing preventing stochastic analyses to be done depending on the study horizon in order to evaluate the potential risks.

As the preceding chapters show, a flood with the same peak flow can have very different consequences for a given system. Good forecasting of inputs and proper management of the water system can limit the consequences of an event.

Appendix A presents case studies provided by the committee’s members.

TO CONCLUDE

We all know that there is room for improvement in the field of dam safety. In the field of hydrology and flood assessment, we must face phenomena continuously changing. We must rely on the data of the past, our present and imperfect knowledge of the phenomena involved and the trends we anticipate for the future to assess the risks we must face. Some of these elements are more obvious, such as:

Climate changes :

- Non-stationarity of the various aspects related to flood assessment;
- The difficulty of establishing the impacts of climate change for extreme events or for combinations of events;
- The probabilities related to the different scenarios studied.

The uncertainties related to the analyzes carried out:

- Limited information mainly for extreme hydrological conditions and for combinations of various conditions (including hydrological conditions, mechanical failures, human factors and others).
- The links or correlation between these parameters;
- The different ways to take into account uncertainties, including:
  - Security factors;
  - Assumptions and approximations;
  - and others

Some of these elements will be addressed in the next bulletin, where they may be addressed by or in partnership with other committees. This applies more specifically to all aspects of climate change that require expertise beyond the scope of this committee.

In conclusion, we could say that we must continue to progress in the field of dam safety. With respect to this committee, we need to continue to develop our knowledge in flood assessment for dam safety and related events that may endanger dams and hydraulic structures. Each step forward shows us that our knowledge and tools are limited, but we must look to the future, since we still have so much to learn.

As Albert Einstein said : « *Learn from yesterday, live for today, hope for tomorrow. The important thing is not to stop questioning* ».

2. FLOOD VOLUME

2.1. INTRODUCTION

Uncertainties in the determination of floods sometimes substantially affect the design of hydraulic structures. A common source of errors is due to the imprecision of hydrological measurements. Another source, of different nature, may also lead to serious biases, not being safe from inconsistencies. It is closely linked to the treatment and interpretation of the recorded data.

Flood determination usually includes the definition of the river flow hydrograph during and after a storm. The attention usually focuses on the peak of the flood and not so much on its volume; the recession behaviour of the river flow is accepted as is, in general without further consideration. The river base flow at the beginning of the flood draws even less attention.

These elements however play an important role in the intensity of the flood and the overall shape of its hydrograph.

2.2. GENERALITIES

Flood determination through stochastic approaches is one of the main trends to evaluate floods occurring on a specific drainage area. Stochastic approaches for flood determination are reviewed in chapter 3 of the present bulletin. However, because of the overall resources required for such analyses, these stochastic approaches are preferably performed on major and well-known systems. They would be less attractive to implement on small systems or for new dam projects.

Presently, most of the guidelines of different countries are based on the results of statistical flood analyses or the deterministic evaluation of the PMF. Most of the papers related to the statistical analyses of floods focus, for small drainage areas, on the peak discharge or the determination of the hydrograph for a single rainfall event for small drainage areas. As mentioned by Guillaud (2002):

“The entire discussion so far has focused on flood peak, which is the easiest characteristic on the flood to obtain. Another important characteristic of a flood, perhaps more important than the peak is the volume. However, it is usually difficult to determine the volume of the flood caused by a meteorological event without ambiguity, because of the interference with other meteorological events. An alternative is to define the runoff volume over certain durations (5 days, 10 days, 30 days, …) and to reconstruct a hydrograph for each frequency.

Flood peak is essential to know only for the design of hydraulic structures for projects with no or little storage capacity, for example for run-of-river projects.

When a project comprises a reservoir, it is important to know the volume of the flood in order to take the storage effect into account in the evaluation of the size of the structures."

Similarly, the Canadian Dam Association Guidelines mentioned that *"Statistical analysis is required for estimating the flood peaks and volumes associated with a range of annual exceedance probabilities (AEPs). In addition to the peaks, the volumes and the associated hydrographs for the floods of interest are usually required for reservoir routing or dam-breach and downstream channel routing. This analysis is done on a seasonal basis and is of greater significance for storage reservoirs that have large fluctuations in water levels and are designed to capture spring runoff. For run-of-the-river facilities, only the peak annual flood is usually required."*

It is unlikely that a direct relation between the peak and the volume of specific floods will exist for a particular drainage area, but the two characteristics are correlated. If statistical analyses of peak flood can be performed relatively easily on natural discharge of a drainage area, the challenge increases when the volume of the flood corresponding to a specific frequency (return period) must be determined. In this case, it is not only the maximum annual (or seasonal) discharge that must be considered, but also the volume of the flood, which will depend on the duration of the event and will differ for each event.

For small drainage areas (say, less than 50 km^2), it is very likely that the peak discharge and the volume correspond to similar frequency, since the flood is normally caused by a single rainfall event. For large drainage areas, the situation is more complex, since peak discharge and volume for a specific frequency can depend on a combination of events (such as snowmelt and rainfall event(s), in the northern countries). Another difficulty consists in the spatial and temporal correlation of such events over a large drainage area.

The present section will present an overview on the role of the flood volume for dam safety, including:

- Consideration about flood process;
- Flood recession issues;
- Statistical analyses (peak / flood volume);
- Hydrograph reconstitution (rainfall / complex events);
- Extreme values (flood volume);
- Case studies;
- Recommendations.

2.3. CONSIDERATIONS ABOUT FLOOD PROCESS

When attempting to estimate the river behaviour during an important storm, hydrologists are in general used to focus on the magnitude of the meteorological event. The peak precipitation is considered to play an important role in this respect. However, at least as important as the precipitation intensity is the precipitation volume. The exact timing and location of the storm cell(s) is usually not well known, and formulating hypotheses about their behaviour is no guarantee to gain insight in the phenomenon. Actually, as long as the overall volume and centre of gravity of a storm are correctly determined, the exact location of the storm's cells, their succession and magnitude do not play a determinant influence on the peak discharge of locations further downstream.

Indeed the influence of local and limited meteorological events plays a minor role in the evolution of the catchment runoff. This is especially true if the event location is not situated in the immediate vicinity of the considered river point. Methods not requiring the formulation of particular hypotheses may be not very versatile in their approach and treatment of the phenomenon, but they would present the advantage of limiting the possible biases related to these assumptions. In this sense, sophisticated and detailed methods are not necessary the most appropriate to treat this type of problem.

The inertia of flood processes is quite large – the movement of water masses takes time, especially in the underlaying aquifer. Water exchanges between river and aquifers all along its course play an important role to smooth out the river discharge, either in absorbing water from the river, when this one has a particularly high level, or in feeding it when its flow tends to decrease. The direct correlation between the rainfall and the river regime is disconnected by the transit through the aquifers.

During a flood, a given length of river contains a multiple of the volume of water usually present on the same stretch, even during the high flow season. During a large flood, this multiple can reach large proportions.

2.4. ANALYSIS OF FLOOD HYDROGRAPH

A simplified qualitative, one-dimensional model allows visualizing the behaviour of a flood when aquifer and river exchange water. At each time step, water moves:

- from upstream to downstream in the river (from left to right on the graph below);
- from aquifer to river or conversely, depending on the relative water levels;
- between neighbour aquifers, depending on the elevation of their water tables.

A precipitation of limited extent (in time and space) is postulated at the beginning of the considered area. Since the vast majority of the flood is due to the water collected by the watershed, it is assumed that the totality of the precipitation is absorbed by the aquifer, to be transferred later to the river (there is no overland flow). To keep the calculations simple, no losses are considered.

Figure 2.1 illustrates the progression of the wave in time and space.

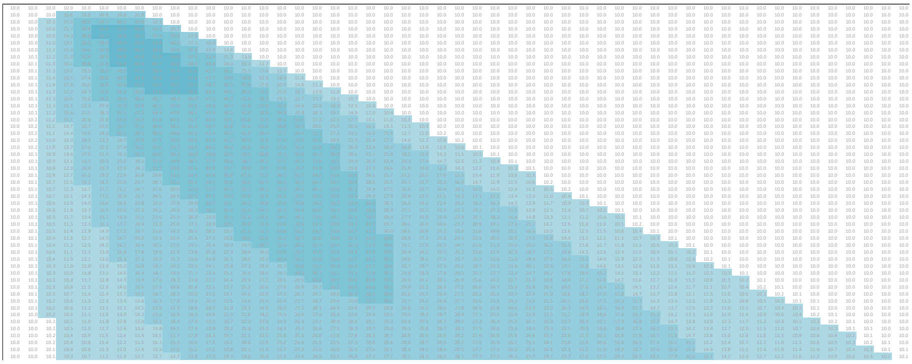

Figure 2.1 Simulated floods with water exchanges aquifer-river

The water volume of the flood in of course conserved as long as the flood wave has not hit the downstream boundary of the model.

To evaluate the behavior of the system, three storms have been postulated, with identical precipitation volume but different precipitation patterns. They extend on respectively seven, five and three stretches of river and the precipitations occur at the same period. Their centre of gravity along the river is similar:

-	Storm 1	120	120	120	120	120	120	120
-	Storm 2		168	168	168	168	168	
-	Storm 3			280	280	280		

For this case, Figure 2.2 represents the three hydrographs of the resulting floods in the river at a section close to the downstream extremity of the first storm. Despite the qualitative nature of the model, it is possible to see that the peak timing and peak magnitude are fairly similar, despite the important dispersion of the precipitation in space (ratio of extension 1 to 2.3) and in magnitude (2.3 to 1). The magnitude of the peak remains in a range narrower than +/– 5%. The volumes have been conserved.

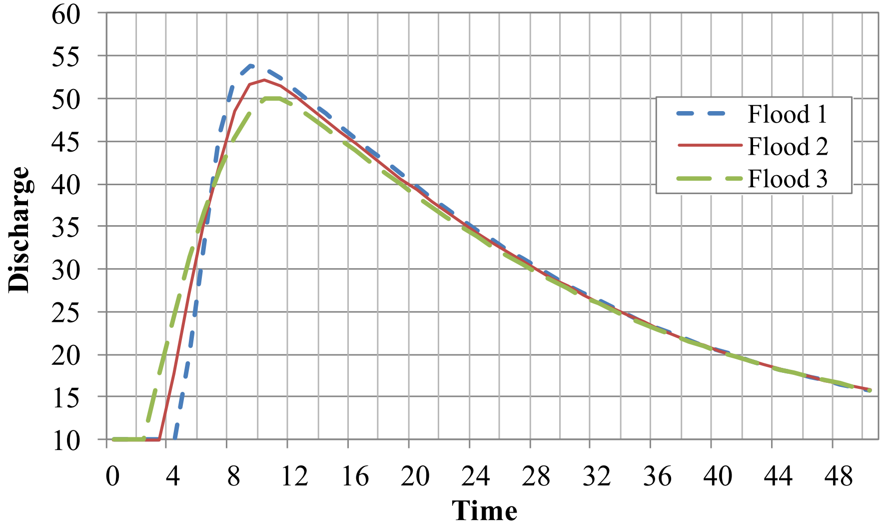

Figure 2.2 Flood hydrographs from rainfalls of various extents, same volume

Another scenario can be considered, postulating the same spatial extent for the storm, but a different pattern of precipitation. For this scenario, three storms of equal volume are also considered, but with various distributions of their intensity along the river.

-	Storm 1	100	200	300	400
-	Storm 2	250	250	250	250
-	Storm 3	400	300	200	100

Figure 2.3 illustrates that the influence of the precipitation pattern is not so determinant for the timing or the magnitude of the peak flow. Despite ratios of 1 to 4 (resp. 4 to 1) for the extremity's precipitations, the three maximum flows lay in a range narrower than +/– 5%.

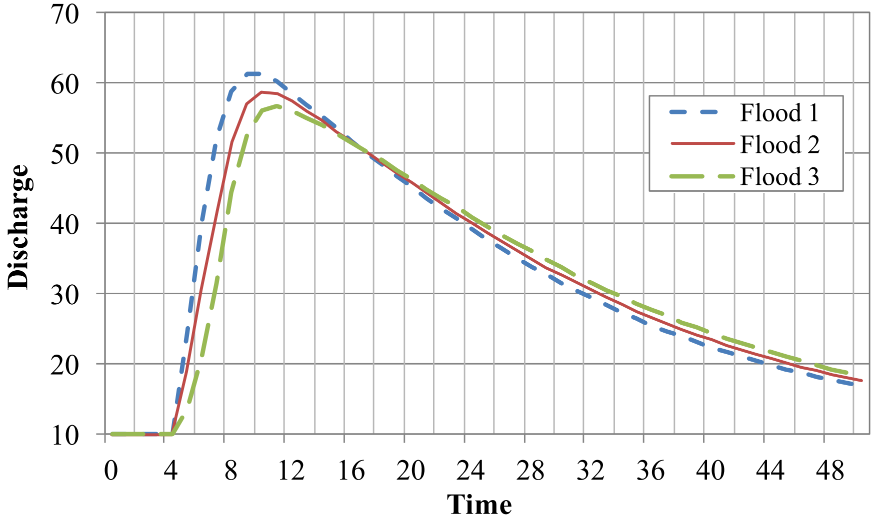

Figure 2.3 Flood hydrographs from rainfalls of various patterns, same volume

A last scenario evaluates the influence of the storm volume on the river response. The spatial extent of the storm is again identical in all three cases, and the precipitation rate is uniform. The volume varies of +/– 20% around a reference value.

-	Storm 1	120	120	120	120
-	Storm 2	100	100	100	100
-	Storm 3	80	80	80	80

Figure 2.4 clearly indicates a different type of river response, at short distance downstream of the storm area. The variation range of the precipitation volume is mirrored in the various river peak discharge: the range of the peak flow reaches abourt +/– 12% of the central value.

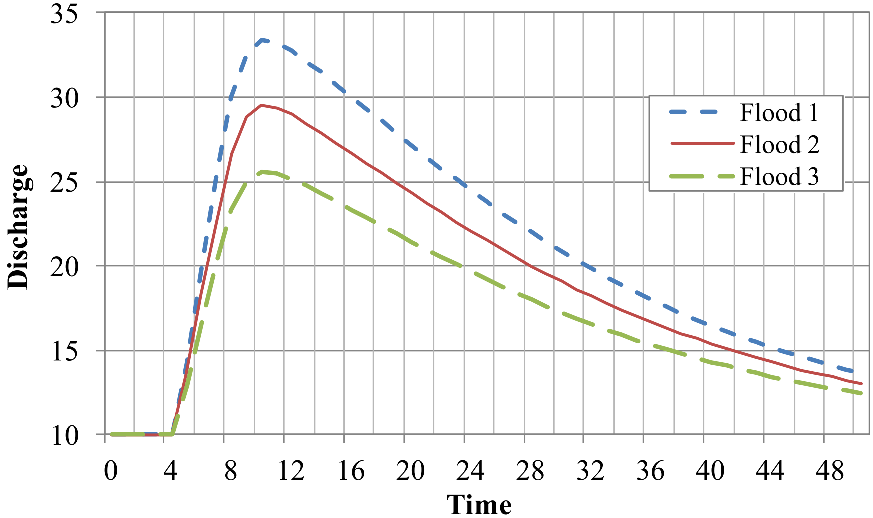

Figure 2.4 Flood hydrographs from rainfalls of same pattern, various volumes

The main learning from these simulations is that the detailed precipitation pattern is not overwhelmingly significant for the river response. The pattern may show a fairly broad variation range without fundamentally impacting on the timing and magnitude of the resulting flood, as long as the total volume of rainfall is identical. More sensible however is this river response on the precipitation volume.

2.5. FLOOD RECESSION ISSUE

The knowledge of the subterranean world is so fragmented and limited that an exact (or at least a reasonably representative) modelling of all sub-catchments is virtually impossible. Similarly, an insight in the detailed precipitations pattern is not everywhere possible. A very valuable indication however is given by the results of the combined effect of all sub-catchments and their tributaries on the river flow at the outlet of the watershed. One observes that this overall reaction, all things considered and all meteorological situations experienced, is fairly regular and repetitive.

For a given river flow, the recession pattern of the flood is nearly always the same, and this independently from the magnitude of the preceding peak flow. This can be interpreted by the fact that, the river flow being essentially driven by the underground water (except perhaps during the peak flow period, when surface flow prevails), a specific river discharge corresponds to a given (yet unknown) combination of aquifers water storage.

2.5.1. Chiumbe River - Angola

Figure 2.5 pictures the behaviour of the Kwanza river in Chiumbe (Angola); its watershed area is about 115 000 km². Clearly visible are the gradual – yet irregular – increase of the river discharge during the rainy season, the yearly peak reached during a storm occurring after the river has significantly grown up, and the recession patterns following the various peaks. The zoomed area on the right of the figure shows the great similarity of all recessions. Several are perturbed by late precipitations of the rainy season. Without however these rainy events, their recession behaviour is quite regular, as for the curve highlighted by green circles, from the peak time until the occurrence of a last strong rainfall event, and even beyond this moment.

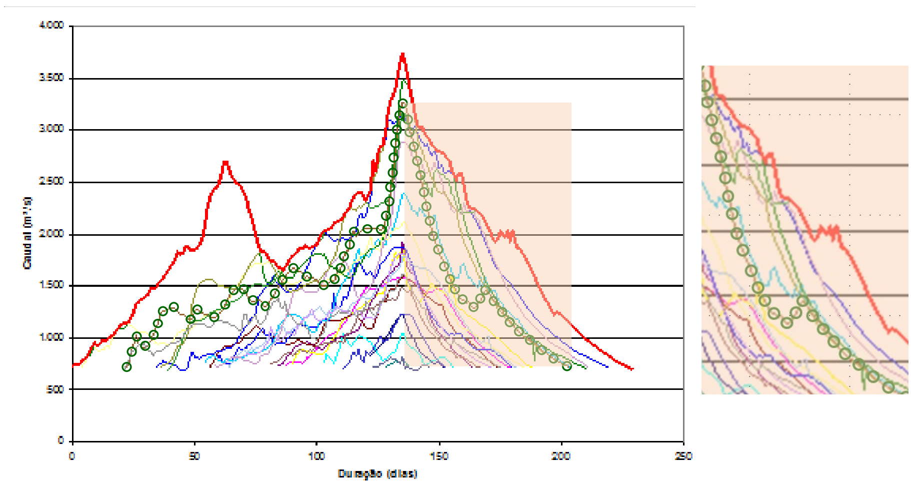

Figure 2.5 Chiumbe River – Flood Hydrographs and Recession Patterns

Actually, the recession behaviour of the entire watershed is only minimally influenced by the magnitude of the peak flow during the rainfall season. As long as it is not interrupted or perturbed by a late precipitation, the recession is almost identically repeatable. The highlighted line shows that, for the discharge value 1500 m³/s, the slope of the recession curve just before the last precipitation event and the resumed recession just at the end of the storm are virtually identical.

In a sense, this line (offsetting the intermediate precipitation perturbation) can be seen as a signature of the watershed. This signature materializes the overall behaviour and (unknown) inter-relationships of all aquifers and tributaries of a river when the aquifers can aliment the river with their water into the river without being perturbed by new rainfalls. It integrates all the internal (and unknown) processes of the watershed and appears to be largely independent from the history of the flood. Due to the location of this river, snow did not play any role in its hydrograph.

The knowledge of this typical recession pattern provides a fundamental hint to the underground behaviour of a watershed. Of course, the exact description of all spatio-temporal characteristics and behaviours of this inner world is probably bound to remain inaccessible. But its signature is easy to determine; it indicates in an all-integrated way how the entire water catchment would typically behave as soon as its aquifers would be filled with water. This reaction would directly lead to know the evolution of the discharge that can be expected at a point of interest along the river.

2.5.2. Mistassibi River - Canada

In Northern areas, the spring flood (mainly caused by snowmelt) is very often the largest annual flood, at least for its volume and very often also for its peak discharge. This type of flood can extend over several weeks, depending of the depth of the snowpack, the air temperature, the size of the drainage area and the rainfall events during this period.

Figure 2.6 illustrates typical large flood hydrographs on the Mistassibi River (Canada), with a drainage area of about 9 300 km². On the Mistassibi River, the spring flood occurs during a period of six to eight weeks; it can even reach twelve weeks from the beginning of the snow melt to the end of the recession. As shown on Figure 2.6, the main flood was observed on 1976. Depending of the sequence of temperature observed, the timing of the peak discharge can vary by six weeks from one year to the other.

Even if the local conditions are quite different from the conditions observed on the Chiumbe River, the flood hydrographs present similar patterns, i.e. the increase of the flow until the peak discharge is reached varies significantly between the floods; however, the slope of the recession pattern is quite similar (except for periods when rainfall is observed).

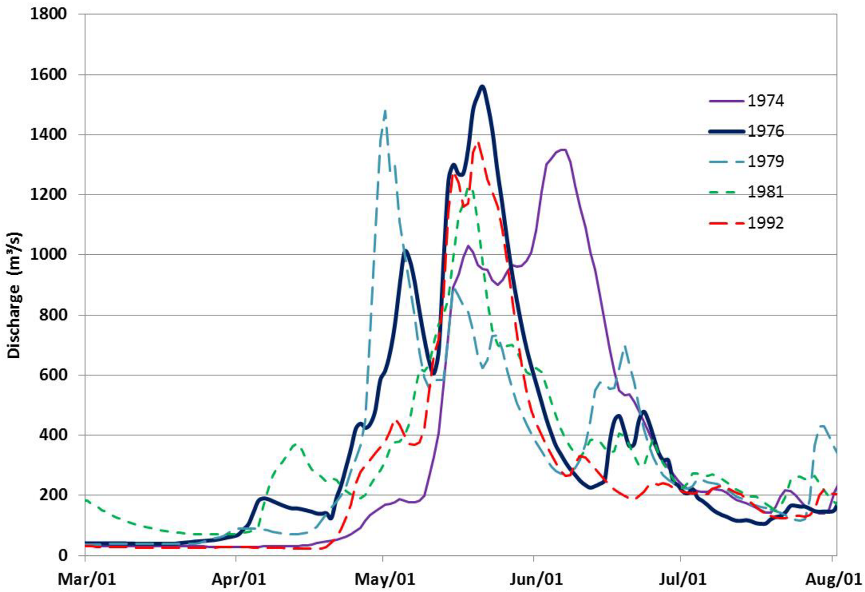

Figure 2.6: Mistassini River – Typical Spring Flood Hydrographs

An attempt of catching the behaviour of the 1976 flood with a simple numerical model based on the recession curve is presented in section 2.6.

2.6. FLOOD VOLUME – STATISTICAL ANALYSIS

Peak discharge and flood volume for specified durations can be estimated through statistical analysis. This is particularly true when most of the flood volume is generated by snowmelt (so-called "spring flood"). As mentioned previously, statistical flood analyses can be performed for different durations (e.g. 5, 10, 30, 45, 60, 90 days) to allow for reconstituting one or several hydrographs for a specific frequency of the spring flood.

Statistical analyses can also be performed on the total duration of the spring flood; however, the criteria to determine the beginning and the end of the flood cannot be determined with certainty if the flood depends on more than one single event. If the beginning of the spring flood corresponds to an increase of the temperature to start the snowmelt process, the end of the spring flood is often difficult to establish, since rainfall events and the characteristics of the drainage area can have an impact on the overall process. Another alternative consists in evaluating the flood volume observed between two specific dates (e.g. between March 15th and June 15th) and perform the statistical analysis based on this assumption.

A statistical analysis of the flood volume was performed on the discharge observed on the Mistassibi River (Quebec, Canada). This river is unregulated, which gives the possibility to observe the characteristics of the flood.

Figure 2.7 presents an example of a statistical analysis of the spring flood maximum daily volume for the Mistassibi River. This figure presents the observations available on this river (51 spring floods) and the lognormal relation proposed to estimate the maximum daily volume.

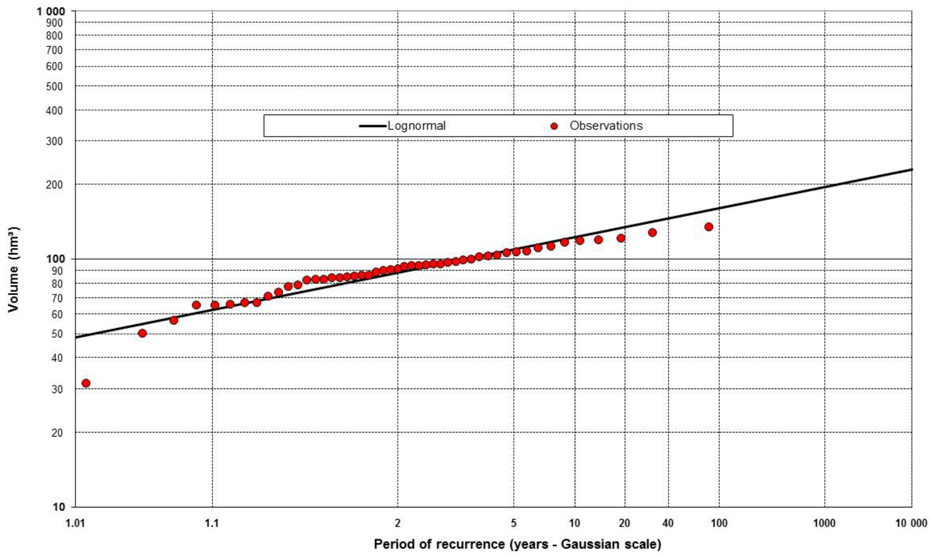

Figure 2.7: Mistassibi River (1963-2013) –
Spring Flood Maximum daily volume – Statistical analysis

The same exercise can be repeated for different durations; Figure 2.8 illustrates the estimated volume of the spring flood for different periods of recurrence and durations[1]. For this case, the durations vary from one day (daily maximum volume) to 90 days.

1 For this exercise, a lognormal distribution was considered, but any other statistical distribution could have been used; the conclusions should remain unchanged.

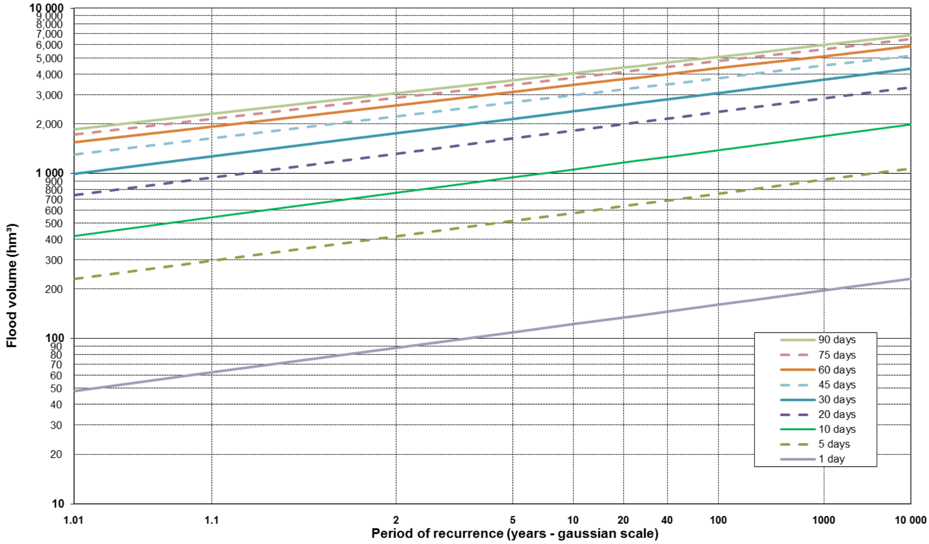

Figure 2.8: Mistassibi River – Spring Flood Volume – Statistical analysis

Figure 2.9 presents the same information, but considering the duration in the X axis. This figure illustrates the variation of the flood volume over time.

Based on this information, it should be possible to prepare a hydrograph respecting the characteristics of the flood for a specific period of recurrence.

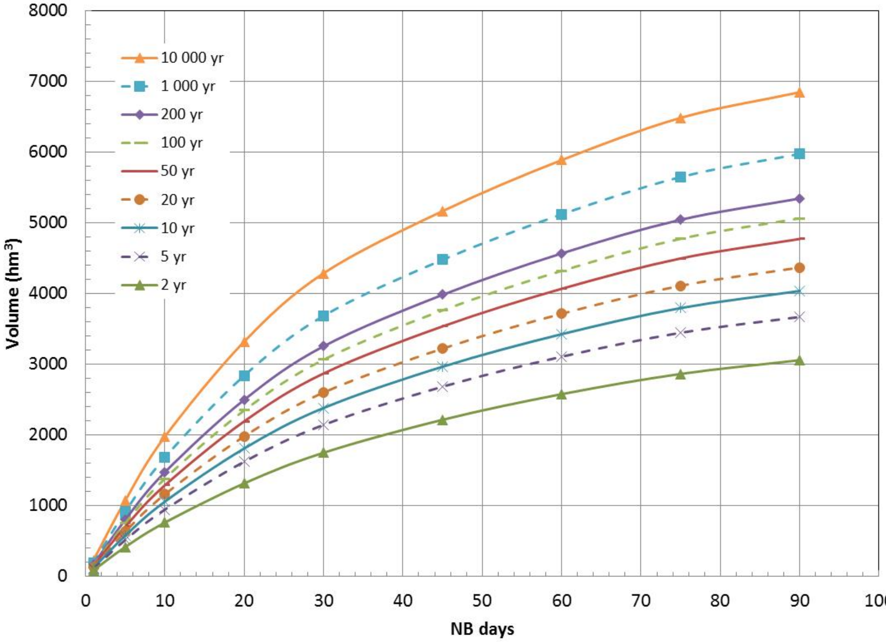

Figure 2.9 Mistassibi River – Spring Flood –Volume vs Number of days

2.7. HYDROGRAPH RECONSTITUTION – RAINFALL EVENT(S)

A method is presented here that considers the flood volume as a central factor of the flood estimation. The method seeks the river response that fits both the net precipitation volume and the recession pattern. The initial base flow plays a non-negligible role in the disposition of the flood.

The method reveals to be robust; examples below illustrate the respective influence of the key factors (precipitation volume, recession pattern, base flow) on the shape of the hydrograph. Two of the most conspicuous advantages of the method are its simplicity of use and the high consistency of the estimated river flow, in particular with the magnitude of the storm at the origin of the flood and the observed recurrent river behaviour.

The flood pattern is usually considered as an added discharge over the river base flow. Various methods help estimate the shape and magnitude of the peak. Conceptually, floods are thus commonly seen as superimposed on top of the naturally receding base flow, as illustrated on Figure 2.10 (left). Very often, the base flow is even considered to remain constant over the duration of the flood and beyond (or even to grow during the flood). The total duration of the added flood and its volume are not always clearly determined. In addition, the junction between the end of the flood and the base flow is somewhat unclear.

Another approach considers that the amount of water brought by the storm perturbs the natural recession of the river flow by increasing its discharge, as seen on Figure 2.10. After peaking, the river flow recedes and reaches again the level it had at the beginning of the flood. It is legitimate to consider that, as long as no new precipitation occurs, the recession occurring beyond this point corresponds to the usual natural base flow recession, as if no flood had occurred (Figure 2.10 right). In this sense, the flood can be seen as a temporary intercalation of additional water during the general recession process of the river flow. Flood volume and duration can be exactly calculated.

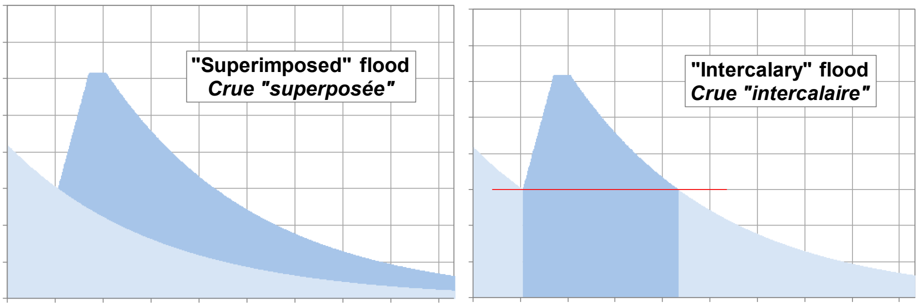

Figure 2.10 Classical (left) and proposed (right) approach to considering a flood

The demonstration of the quantitative equivalence of both models focuses on the two shaded areas of the figure above (and beyond for the superimposed flood). It is assumed that the recession pattern is an invariable response of the watershed and is independent from the history of the flood. On Figure 2.11, the superimposed flood is composed of the partial areas A, B and C; the intercalary flood of the areas A, B and D. The areas A and B being part of both floods, the equivalence of C and D must thus be proven.

The volume of the undisturbed base flow (as if there had not been any flood) consists of areas D and E, from the beginning of the flood until the base flow recedes to zero. The base flow "shifted" by the flood duration is made of the areas C and E. As the recession pattern is invariable and assumed independent from time, as both recessions start from the same discharge (by definition, see horizontal red line), the two receding base flows are strictly equal in shape and define the same water volume.

On the figure, C + E is therefore equal to D + E; the volume materialised by C is hence equal to the volume attributed to D. Finally, A + B + C = A + B + D; both hydrographs correspond to the same volume. This volume represents the net runoff of the flood period, i.e. the total precipitation minus all the losses.

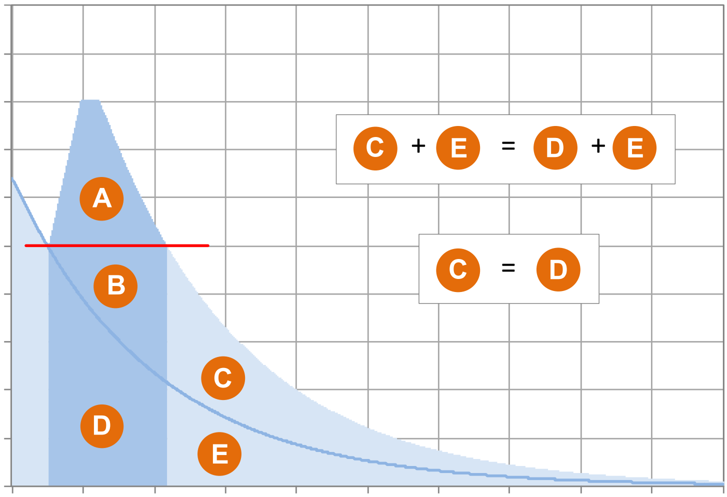

Figure 2.11 Equivalence of the flood volumes

An example of the application of this approach is visible on Figure 2.12. The 1976 flood of the Mistassini River has been simulated by four successive floods, all with an identical recession pattern. For each flood, the river flow and the flood volume have been adjusted in order to fit the observation. The blue area represents the simulated volume of the flood series. The various peaks can be exactly reproduced, in magnitude and timing; the close fit of the recession curves confirms that they belong to the same family. The periods of growing river flow show some small discrepancies due to not considered short rainfall events; in addition, a very last small rainfall early July has not been considered.

To within half a percent, the integration of the blue area indicates a volume of 4’000 x 10^6 m^3. This corresponds to the official estimates.

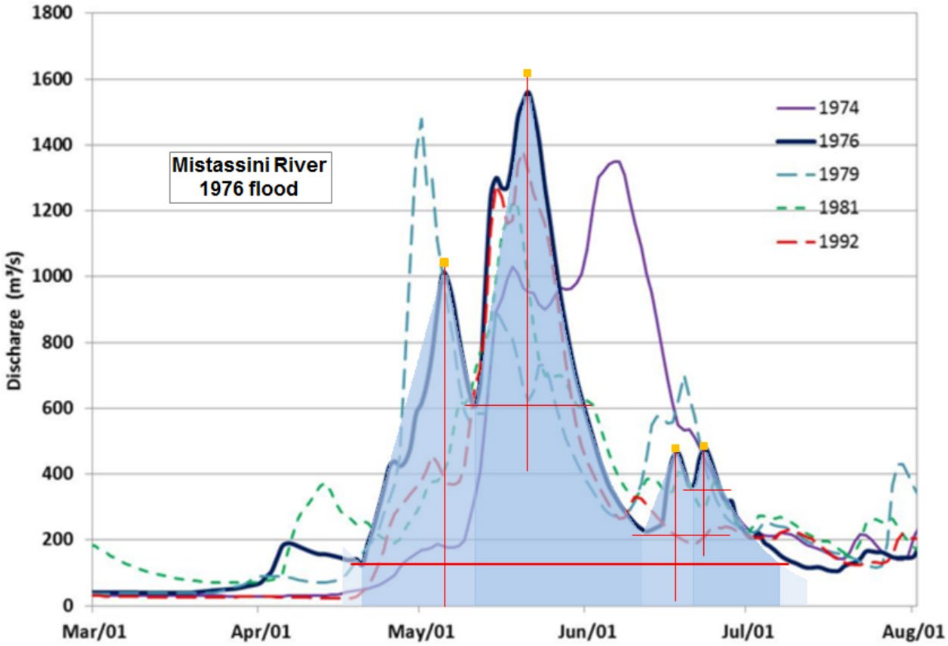

Figure 2.12 Observed and FIM-simulated Mistassini 1976 flood

2.8. HYDROGRAPH RECONSTITUTION – COMPLEX EVENTS

The reconstitution of a flood hydrograph for a specific frequency taking into account the results of the statistical analysis of the peak discharge and the flood volume (for specific durations) can lead to some discrepancies.

An intuitive approach consists in modifying an observed hydrograph considering the results of the statistical analysis to reproduce the peak discharge and the volume of the flood for different duration. Figure 2.13 illustrates this approach based on the largest spring flood observed on the Mistassibi River (1976). These hydrographs respect the peak discharge and the volume estimated by statistical analysis for different durations, however the recession pattern does not respect the pattern observed on historical floods, which is a characteristic of the drainage area.

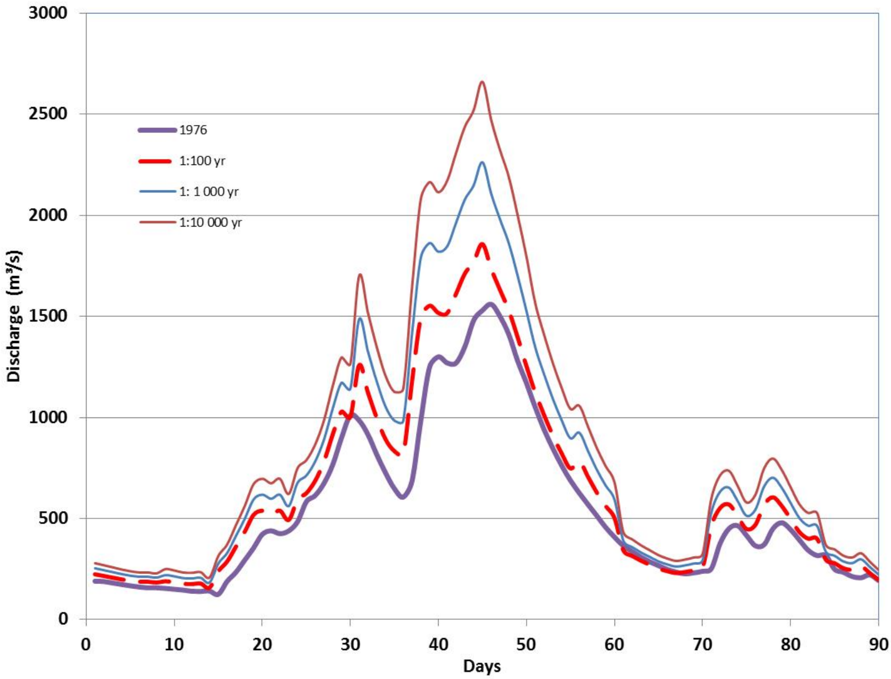

Figure 2.13 Mistassibi River – Spring Flood Hydrograph – Without consideration of recession characteristics

As shown previously in this chapter, the flood recession follows a specific pattern which is independent of the flood duration. Under this assumption, a large flood should take more time to return to the normal conditions than a smaller flood event; this will have an impact on the reconstitution of the flood hydrograph.

Figure 2.14 illustrates the reconstitution of the same flood hydrographs, but this time considering the recession pattern of the drainage area. The flood peak and volume are respected and the results appear more realistic.

It should be noted that such hydrograph(s) is only representative of one possible pattern for specific period of recurrence. Such analyses should be performed with different patterns (for the same period of recurrence) to evaluate the consequences of floods. Intuitively, for systems with relatively large reservoirs, the later the flood peak discharge occurs, the more critical will be the consequences, since the reservoir will be at higher level at the occurrence of the peak discharge.

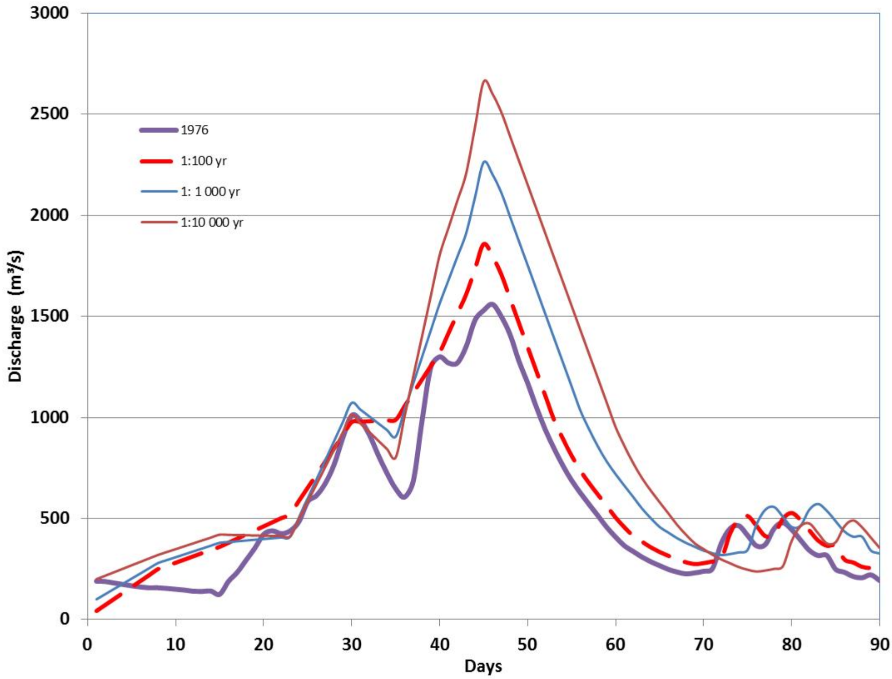

Figure 2.14 Mistassibi River – Spring Flood Hydrograph – With consideration of recession characteristics

2.9. RELATION BETWEEN FLOOD PEAK AND VOLUME

For drainage areas where major floods are caused by a single event, the flood peak discharge and the flood volume could have similar periods of recurrence. However, for larger drainage areas with more complex flood conditions, the situation is different. The longer the flood duration will be, lower should be the correlation between the peak discharge and the volume.

As example, an analysis was performed on the Mistassibi River data. As shown on Figure 2.15, the coefficient of determination (R^2) between the maximum daily volume of the flood (daily peak discharge) and the five-day maximum volume is about 98.2%. It decreases significantly for longer comparison periods.

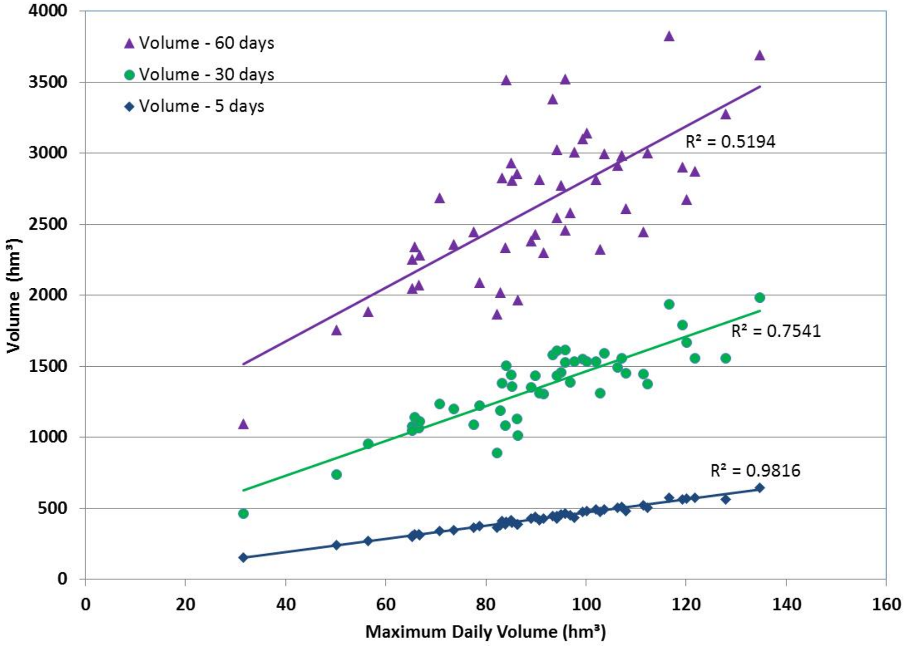

Figure 2.15 - Mistassibi River –
Comparison of the spring flood volume for different durations

It is not possible to generalize conclusions based only on this specific case; however, this shows that precautions must be taken in the reconstitution of the flood hydrograph, since the relation between the peak daily volume and the overall flood volume is not straight forward. It also illustrates the risk of performing an analysis with only one hydrograph, since numerous combinations are possible.

2.10. DETERMINISTIC APPROACH

The flood evaluation for different return periods can be performed using a deterministic approach, particularly for locations where observed discharges data are not available or only for a short duration. Results of the statistical and deterministic analyses of the flood volume for rainfall event(s) should lead to results in a similar range; this is particularly the case for small drainage areas, for which a single rainfall event is usually considered.

A deterministic approach is also mainly used to evaluate the Probable Maximum Flood, considering various possible scenarios maximizing the consequences on the system[2].

The following elements must be considered for applying similar approaches:

a. Main rainfall event

The main rainfall event causing the flood normally corresponds to the expected flood return period; higher is the probability to see such event, higher the number of combinations that can generate a similar flood discharge or volume.

b. Antecedents events

Antecedent events are particularly important to establish the conditions prevailing before the occurrence of the main rainfall event. This will have an impact on the river discharge before the event and, even more important, on the soil moisture. The more saturated the soil will be, the faster the response time of the system will be (increasing the peak but also the volume for a specific duration). A similar situation can be observed if a major rainfall event occurs when the soil is frozen.

Similarly, the base flow does not simply represent a reference river discharge on which the peak flow is added but is an integral in the building up of the flood structure. The net peak (additional discharge over the peak flow) generated by an incoming flood volume is not a constant independent from the inflow pattern.

To evaluate the PMF, a large rainfall should be considered shortly before the PMP to saturate the soil and ensure a maximum runoff.

c. Snow

The snow cover and the snowmelt period will have a direct impact on the flood volume and the peak discharge. Both factors are important, since a rapid snowmelt of a large snow cover will most likely generate large floods. When the snow cover is an important part of the flood volume, the spring flood is very often the largest one of the year, triggered by the combination of snowmelt and rainfall. Deep snow covers increase the likelihood of large floods.

Before melting, the snow cover must be primed by warm temperatures bringing it close to the melting point. A realistic temperature sequence must be developed based on the observed conditions in the drainage area.

d. Subsequent events

Events following the main event can have a significant impact on the flood volume and its duration. The impact of the subsequent events is particularly significant until the reservoir returns to its maximum operation level (MOL). The longer the

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2 The PMF scenario with the maximum peak discharge is not automatically the worst scenario (maximum water level) for a dam with regulation capability. It happens that a spring PMF (with lower peak discharge, but larger volume) reaches a higher water level in a reservoir than a summer PMF (rainfall event).

duration to return to the MOL, the more vulnerable is the system in case of a new large flood.

The subsequent events often occur in period(s) when large discharges have been observed. This is particularly true for the evaluation of the PMF. For floods with lower return periods however, it is not obvious to determine a subsequent sequence of events, since there is in general no direct relation between the main rainfall event and the subsequent events.

e. Initial conditions

Since oftentimes the objectives of such studies consist in determining the maximum water level in a reservoir corresponding to a specific period of recurrence, the initial conditions of the system are an important factor. The expected volume of storage available before the flood will depend of the period of the year. Normally the MOL is considered for a rainfall flood event.

However, for a spring flood (with a large percentage of the flood volume generated by the snow cover), the reservoir level and the mode of operation during the first part of the flood (until it reaches the MOL) will depend on the expected conditions at this time of the year. The volume available for flood routing will be larger; it is therefore unlikely that the spillway will be operated at full capacity at the beginning of the flood. It may even not reach this discharge at all, because of the uncertainty related to the final flood volume.

f. Comments

The evaluation of the flood volume for rainfall event(s) on large drainage areas or for spring flood is complex, since it involves different events or conditions as discussed above. If it is possible to identify the most likely scenario(s) to generate a PMF, the number of scenarios to determine the 1:100, 1:1000 or 1:10,000 year flood is almost infinite, since the combination of events leading to lower return periods depends on too many combinations of parameters.

Comparison of the results from flood statistical analyses of spring flood volume and deterministic analyses of the PMF volume can lead to inconsistencies. For example, the extrapolation of the flood volume for a 1:10,000 year return period can be higher than the volume of the PMF. Some explanation can be proposed:

- The statistical analyses overestimate the flood volume. The number of recorded floods (usually a few tens) considered in a flood extrapolation to the range of 1:1,000 years or more does not always guarantee a high quality estimation, since the trends are not always well defined;
- Some of the parameters used in the deterministic analyses were underestimated (for instance subsequent events). Since a period of analysis of several weeks can follow the PMP, it is difficult to consider realistic rainfall events during this period;
- Most probably a combination of both factors.

2.11. STOCHASTIC MODELING

Stochastic modelling can be seen as an answer to the evaluation of the flood volume, whose results can be compared with those of a stochastic analysis of the flood peak and flood volume or with the deterministic evaluation of the PMF. Stochastic modelling appears to be particularly interesting for floods caused by a set of events (such as the combination of snowmelt and rainfall events) and for systems of reservoirs in cascade. Such modelling will have to reproduce the succession of precipitation and air temperature along the year (to determine if the precipitation will be rain or snow), the flood routing through the drainage area including soil moisture variations, infiltration, losses, snowmelt and the reservoir management (i.e. the operation of the control structures), to determine the maximum water level to be observed at the site(s). Thousands of years will have to be stochastically generated and simulated to estimate the probability related to very large floods.

One of the main challenges in this process consists in representing adequately the statistical distribution of each parameter and the temporal correlations between them, such as:

- The relation and duration between precipitation events;
- The distribution of the precipitation on large drainage areas;
- The relation between air temperature and precipitation (rainfall or snowfall);
- The variation of the air temperature and the snowmelt process (if applicable).

The situation becomes even more complex for large drainage areas, since spatial correlations and sometimes orographic effects at different locations must also be considered. At the same time, the probability of deficiencies in the system and “human” actions can play a significant role in the spatial and temporal evolution of the flood.

The accuracy of the physical model(s) to represent large flood events must also be considered, because of the limitations on the information available to calibrate the model for such large floods. Usually a large number of assumptions (explicit or implicit) are made at the basis of such a model; this of course generates larger uncertainties.

If it is well known that the extrapolation of large floods may be subject to a significant degree of uncertainty[3], because of the limitations of the sample available to fit the statistical distribution. Similar concerns should also be considered about the parameters considered in stochastic modelling and the final results obtained.

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3 CDA Guidelines →“Flood statistics are subject to a wide margin of uncertainty, which should be taken into account in decision-making.”

The use of stochastic modelling to evaluate flood characteristics and the corresponding flood level is discussed in more details in bulletin 170 and in the present bulletin (chapter 3).

2.12. FLOOD VOLUME – EXTREME VALUES

Data of maximum floods observed in several countries around the world date back to 1984, when the International Association of Hydrological Sciences (IAHS) published the “World Catalogue of Maximum Observed Floods”. Also, ICOLD Committee on “Dams and floods “published, in 2003, the Bulletin 125 on Dams and Floods, which contributed with more significant data related to maximum floods, mainly for dams and reservoirs. Recently, in 2014, a new and more extensive review of maximum floods has been carried out on the data of flows and volumes of maximum floods.

For the analysis of the peak discharge, the envelope curves method with the Francou-Rodier (F-R) equation can be used. The F-R equation is the relationship between the peak flow and the catchment area:

$$\frac{Q}{Q_0} = \left(\frac{A}{A_0}\right)^{1-\frac{K}{10}}$$

where:

- Q = Peak flow (m^3/s)
- A = Catchment area (km^2)
- Q_0 = 10^6 m^3/s
- A_0 = 10^8 km^2
- K = Francou-Rodier coefficient

For each peak discharge the coefficient K is calculated by:

$$K = 10 \cdot \left(1 - \frac{logQ - logQ_0}{logA - logA_0}\right)$$

The database on flood volumes comes from the surveys carried out by ICOLD; it consists of 187 records on volume of maximum floods in dams and reservoirs from 15 most significant countries in this field.

The methodology used is similar to that used for the analysis of the peak flows, assessing the relationship between the flood volumes and the catchment area, through the equation:

$$\frac{V}{V_0} = \left(\frac{A}{A_0}\right)^{2-\frac{K_V}{10}}$$

where:

- V = Flood volume (hm^3)
- V_0 = 50×10^6 hm^3
- A_0 = 10^8 km^2
- K_v = Coefficient of flood volume

Therefore, for each flood the coefficient K_v is calculated by:

$$K_V = 10 \cdot \left(2 - \frac{\log V - \log V_0}{\log A - \log A_0}\right)$$

Figure 2.16 shows the relationship between the flood volume and the catchment area for the floods analysed with the available data. It defines an envelope curve of the extreme flood volumes with a value of K_v = 10.5

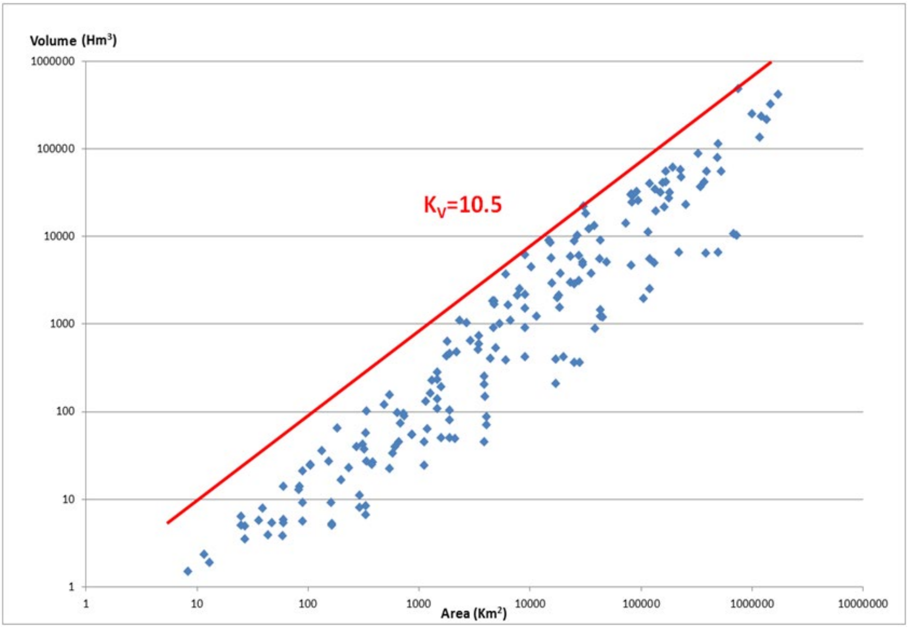

Figure 2.16 – Flood Volumes -
Envelope curve of extreme flood volumes – K_v = 10.5

The highest value was in Brazil (Tocantis reservoir) with a K_v= 10.5, in a 1980 flood.

Figure 2.17 shows the relationship between specific volume and the catchment area. The specific volume, a measure of the volume generated per unit of the catchment area, is expressed by :

$$V_s = \frac{V}{A}$$

where:

- V_s = Specific volume (mm)

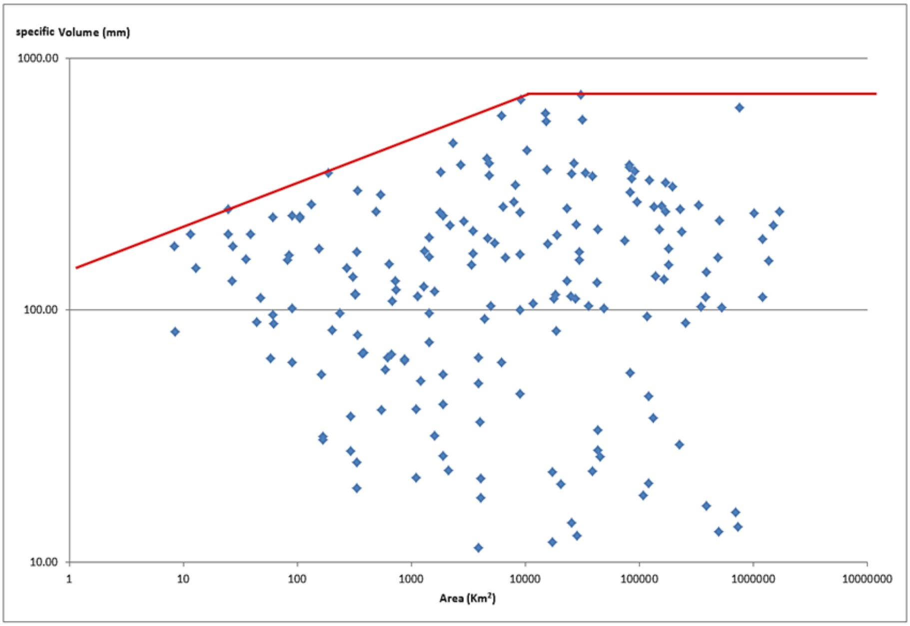

Figure 2.17 – Relationship between specific volume (V_s) and catchment area

It should be noted that there is no systematized database on flood volumes around the world. The results presented are a preliminary analysis, which should lead to prepare a more detailed database of flood volume. Such database can be used to perform initial evaluation of flood volumes on drainage areas presenting similar conditions, mainly for validation purposes. It should be further expanded in the future.

2.13. IMPACT OF CLIMATE CHANGE ON FLOOD VOLUME

It is widely recognized that climate change will increase the variability of extreme events. The increase in air temperature will have an impact on the maximum rainfall that can be observed in several regions of the world; this will in turn have a direct impact on the floods peak discharge and the flood volume.

In the northern areas and for spring floods, the impact on the volume of the major floods will be generally less important on the spring flood than the impact on the peak flows, since for a watershed, projected reductions in the snowpack volume may partially offset the expected increases in rainfall (Ouranos 2015). In this case, the volume of the flood could be similar but it may occur over a shorter period, since the snowmelt season will possibly be shorter (which could lead to higher peak discharge). However, this conclusion cannot be generalized because the regional conditions can change significantly over the world. Some recent meteorological events will probably have some impacts on our understanding of their characteristics and of their consequences[4].

2.14. RECOMMENDATIONS

- Representing adequately the volume of the design flood and considering this volume in the design of the dam and its hydraulic structures is essential to adequately consider the storage effect of the reservoir and to optimize the size of the structures. Whatever the approach selected to evaluate the flood hydrograph, an estimate should in any case check the volume of the resulting flood and validate it comparatively with the precipitation/snowfall volume.
- The recession of the flood is not depending on the peak discharge, but on the characteristics of the drainage area and the river; it is important to respect the recession pattern in the hydrograph reconstitution.
- For a same peak discharge and a same flood volume, the shape of the hydrograph can have an impact on the maximum level in a reservoir (depending of the operation rule of the reservoir). It is important to perform a sensitivity analysis on the shape of the hydrograph. Intuitively, a hydrograph with a late peak discharge could have more impact than a hydrograph with an early peak discharge, since the reservoir could then be at a higher level.
- For precipitations concerning an entire water catchment, an estimate based solely on the precipitation volume and the watershed signature may give worthwhile indications to cross-check the results of traditional estimation methods.
- There is no guarantee that a direct relation can be found between the peak discharge and the flood volume for floods deriving from a combination of events (such as a flood from snowmelt). However, without further information, a conservative assumption will be to consider that the 1:N-year peak discharge is corresponding to the 1:N-year flood volume for any duration.
- Reconstitution of a flood hydrograph must respect the physical characteristics of the drainage area; the recession period of the hydrograph follows a pattern independent from the flood magnitude.

[4] For example, Hurricane Harvey released about 1300 mm of rain in the Houston area (USA) in 2017. The hurricane remained stationary for a few days, moved away from the area and came back a few days later.

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3. STOCHASTIC APPROACH TO FLOOD HAZARD DETERMINATION

3.1. INTRODUCTION

The traditional concept of the Inflow Design Flood (IDF) has been and is still being used to size the dam and its designated flood discharge facilities (i.e. spillway, low level outlets) so that the dam could safely pass either a flood of pre-determined probability of exceedance or the Probable Maximum Flood (PMF). The IDF standard is directly linked to the dam hazard classification so that low hazard dams are designed using smaller IDF than high hazard dams. For high (or extreme) hazard dams, two general world trends have developed (ICOLD, 2003):

1. USA, UK, Canada, Australia and countries under their economic and technological influence use the PMF methodology. The PMF is defined as the most severe “reasonably possible” combination of rainfall, snow accumulation, air temperatures, and initial watershed conditions. The PMF is a deterministic concept and its probability of occurrence cannot be determined. Theoretically, it represents the upper physical flood limit for a given watershed at a given season. In reality, PMF estimates are typically lower than the theoretical upper limit by some variable amount that depends on the available data, the chosen methodology and the analyst’s approach to deriving the estimate (Micovic et al., 2015).

2. Most European countries use probabilistic methods to derive an inflow flood characteristic (typically peak flow of certain duration) with return periods ranging from 1,000 to 10,000 years.

For lower-hazard dams, the IDF selections criteria vary but typically include either a percentage of the PMF or return periods shorter than 1,000-years (ICOLD, 2003).

In recent years, an increasing number of dam owners have started to apply various forms of risk informed decision making process in their dam safety assessments regarding flood hazard. For example, the IDF selection guidelines published by US Federal Emergency Management Agency (FEMA, 2013) suggests that besides the traditional prescriptive approach to IDF selection, a risk- informed hydrologic hazard analysis should be carried out at the discretion and judgment of dam safety regulators and owners ‘‘for dams for which there are significant trade-offs between the potential consequences of failure and the cost of designing to the recommended prescriptive standard’’. The guidelines suggest that an integral part of risk-informed hydrologic hazard analysis is the development of hydrologic loads that can consist of peak flows, hydrographs, or reservoir levels and their annual exceedance probabilities (AEP). Another example is the latest guidelines by Australian National Committee on Large Dams on selection of acceptable flood capacity for dams (ANCOLD, 2017). While the guidelines retained the PMF concept as part of a simplified risk procedure for extreme hazard dams, there is a clear emphasis on risk assessment even for the cases when the PMF needs to be derived, it is recommended that its “reasonableness” be considered and assessed using the procedure outlined in Nathan et al. (2011) so that the degree of conservatism implicit in the PMF is justified and properly aligned with dam safety decisions regarding potential dam upgrade costs.

Note that risk informed approach to flood hazard for dam safety implies knowing the probability of dam overtopping due to flood. This practically means that the full probability distribution of reservoir levels needs to be derived so that the exceedance probability of the reservoir level corresponding to the dam crest could be quantified. The IDF standard is necessary for sizing the surcharge storage, height of a dam and outlet works, and could be useful in assessing safety of dams with fairly steady reservoir level (where a full pool assumption is not unreasonable) and without active discharge control systems such as gated spillways or low level outlets. However, in regard to individual dams or dam systems with fluctuating reservoir elevation and active discharge control systems, the IDF concept is inadequate for use in flood hazard risk assessment analyses.

For those types of dams and dam systems, the IDF, by characterizing inflow to the reservoir, does not provide the necessary information (i.e. magnitude and probability) on the flood hazard in terms of hydraulic forces acting on the dam itself (peak reservoir level). The commonly used solution for this problem is to route the IDF through the reservoir and determine the resulting peak reservoir level, and thereby obtain at least some information (magnitude but not probability) on the flood hazard acting on the dam. In addition, the IDF concept typically assumes that, during an extreme flood, everything operates according to the plan, i.e. accurate reservoir level measurements, spillway gates open as required, necessary personnel available on site, communication lines fully functioning. In other words, the IDF concept does not address possibility of “operational flood” in which a dam could fail due to a combination of a flood that is much smaller than the IDF and one or more operational faults.

The number of possible combinations of unfavourable events causing such a failure is very large and increases with the complexity of the dam or system of dams. Consequently, the probability of dam failure due to an unusual combination of relatively usual unfavourable events, which individually are not safety critical, is larger than the probability of dam failure solely due to an extremely rare flood. Baecher et al. (2013) stated that, for a complex system such as flow control at a dam, the number of possible combinations of unfavorable events is correspondingly as large as the probabilities of any one combination occurring is small. As a result, the chance of at least one pernicious combination occurring can be large. There are many examples of “operational flood” failures; two North American examples are illustrated below:

- Canyon Lake Dam on Rapid Creek in South Dakota failed on June 9th, 1972, resulting in 238 fatalities. The reason for the dam failure was not the lack of flood passing capacity but the inability to use the spillway which was clogged by debris.

- Taum Sauk Dam in Missouri overtopped and failed on December 14th, 2005. The reason for the overtopping was not high inflow but the error in reservoir level measurement (the pressure transducers that monitored reservoir levels became unattached from their supports causing erroneous water level readings, i.e. reported reservoir levels that were lower than actual levels). In addition, the emergency backup reservoir level sensors were installed too high, thereby enabling overtopping to occur before the sensors could register high reservoir level.

Clearly, risk informed decision making for dam safety requires more than the IDF concept. In order to have any scientifically-based idea of the probability of dam overtopping due to floods, it is necessary to focus on estimating probabilities of peak reservoir level. The process can be described as follows:

- The reservoir inflow of a certain probability of exceedance is only the starting value that gets modified by a complex interplay of starting reservoir level, reservoir operating rules and decisions, and reliability of discharge facilities, personnel and measuring equipment on demand.

- At the end of the process, the reservoir outflow and associated peak reservoir level have different exceedance probability than the reservoir inflow that started the process.

- The exceedance probability of the peak reservoir level is what determines the probability of dam failure due to flood hazard; the probability of the reservoir inflow is no longer the major driving parameter, but only one of the inputs needed to calculate the probability of the peak reservoir level.

Note that the peak reservoir level, unlike the reservoir inflow, is not a natural and random phenomenon and its probability distribution cannot be computed analytically (e.g. by using statistical frequency analysis methods). The probability of the peak reservoir level is the combination of probabilities of all factors that influence it, including reservoir inflows, initial reservoir level, reservoir operating rules, system components failure, human error, measurement error, as well as unforeseen circumstances. Thus, the approach to estimating the full probability distribution of the peak reservoir level consists of some kind of stochastic simulation that includes as many of these factors and scenarios as possible. It is a complex multi-disciplinary analysis which is currently beyond technical capabilities of some dam owners. However, without it, the proper risk-informed dam safety management is not possible. The main goal of stochastic simulation approach to flood hazard is to carry out probabilistic analysis of various flood characteristics (inflow, outflow, peak reservoir level) resulting from floods on a dam system and derive the continuous probability distributions which could then be used to evaluate exceedance probabilities of various reservoir levels including the level corresponding to the dam crest (dam overtopping level) as well as the level resulting from the PMF. That way, different design criteria could be considered and evaluated at various flood frequency levels, thereby departing from widely used strict “pass/fail” deterministic design criteria.

3.2. BASIC PRINCIPLES OF STOCHASTIC APPROACH TO FLOOD HAZARD

In deterministic approaches, a particular flood characteristic (e.g. inflow, outflow, routed reservoir level) is the result of a fixed combination of meteorological, hydrological and reservoir routing-related inputs. For instance, the peak reservoir level resulting from the PMF is derived using a fixed combination of the following inputs:

- Rainfall magnitude and its spatial and temporal distributions over the watershed (typically provided in form of Probable Maximum Precipitation)
- Initial snowpack accumulation within the watershed
- Air temperature sequence during the PMF event
- Initial soil moisture content of the watershed
- Initial reservoir level
- Availability and operating sequence of discharge

On the other hand, stochastic approaches treat those inputs as variables instead of fixed values considering the fact that any flood characteristic could be caused by an infinite number of different combinations of inputs. The variation of the flood-producing input parameters is achieved by stochastic sampling either from empirical distributions or from theoretical probability distributions fitted to observed data. Note that most stochastic flood analyses assume process stationarity, i.e. probability distributions of input parameters are not changing over time. Consequently, they do not capture potential changes in hydrometeorological parameters and their inter-relationships that could result from long-term climate change.

Another thing that all stochastic approaches to flood hazard for dam safety have in common is the use of a deterministic watershed model (i.e. rainfall-runoff model) to convert rainfall and snow/glacier melt into watershed runoff, which ultimately becomes the reservoir inflow. In terms of watershed model simulation, the stochastic flood hazard methods could employ:

- Event-based simulation where a watershed model is used to convert rainfall storm event of certain probability into a flood hydrograph (typically 3-7 days duration). Initial watershed conditions such as soil moisture content and snowpack accumulation have to be assumed and described stochastically.

- Continuous simulation where watershed model is used to convert historical or synthetic rainfall time series into a continuous reservoir inflow record from which flood events of interest can be directly extracted. In this case, initial watershed conditions are continuously accounted for by the watershed model, which is an obvious advantage over event-based simulation approaches.

Boughton and Droop (2003) presented a review of continuous simulation for design flood estimation. Despite their theoretical advantages, it should be noted that continuous simulation models face the challenge of model complexity needed to accurately represent the full range of watershed runoff, from droughts and low flows to very large floods typically needed for dam safety applications. Nathan (2017) provided an excellent discussion on some particular issues that should be carefully considered prior to using continuous simulation models to derive flood frequency curves over a probability range of relevance to dam safety (i.e. return periods of 1,000-years and beyond). An example of continuous simulation used for design flood estimation is the GRADE method (Hegnauer et al., 2014) developed in the Netherlands and used to derive design discharges for the rivers Rhine and Meuse with drainage areas of 165,000 and 21,000 km^2, respectively. Stochastic weather generator based on the nearest-neighbour resampling is used to produce rainfall and temperature series that preserve statistical properties of the original, historically observed data. Synthetic rainfall and temperature data are generated at multiple locations simultaneously in order to preserve their spatial distribution over the watershed, without making assumptions about the underlying joint distributions. The continuous record of 50,000 years of daily weather data is simulated using a simple nonparametric resampling technique where daily rainfall amounts are resampled from the historical record (56-year for the Rhine basin; 73-year for the Meuse basin) with replacement.

Note that this approach does not generate daily rainfall amounts greater than those observed in the historical record; however, the technique of resampling with replacement creates different temporal patterns resulting in multi-day rainfall amounts higher than those observed in the historical record. A watershed model is used to calculate runoff from this synthetic rainfall and temperature series, and the runoff is then routed using a hydrodynamic model to account for complexities associated with retention and flooding along particular river stretches. This procedure yields the continuous record of 50,000 years of daily discharges at or near the points where rivers Rhine and Meuse enter the Netherlands. Finally, the flood values for the various return periods are obtained by ranking the annual maximum discharges in the generated 50,000-year sequence in the ascending order, where the rank in this ordered set determines the return period. The main source of uncertainty in the GRADE method is the relatively short length of the historical precipitation and temperature series used in the stochastic weather generator. Using less than 100 years of historical data to generate 50,000 years of synthetic data affects the ability to accurately capture year-to-year variability over the long periods of time. For instance, resampling from a relatively wet baseline series will result in relatively wet long-duration synthetic series, which in turn will increase uncertainty associated with derived flood discharge values, especially for higher return periods. This large uncertainty is reflected in the GRADE flood frequency results for the Meuse River, where the best estimate of 10,000-yr flood of 4,400 m^3/s is given with the 95% uncertainty range of 3,250 to 5,550 m^3/s.

Finally, there are stochastic approaches that fit somewhere in between event-based simulation and continuous simulation – they could be called semi-continuous or hybrid approaches. They utilize a watershed model that has been calibrated to satisfactorily represent hydrological behaviour of the watershed over a long continuous period for which historical record of climate input data is available. This creates a continuous database of watershed initial conditions which can be stochastically sampled at any time/season of the year and combined with a rainfall event of a certain duration and probability, sampled from rainfall magnitude-frequency curve. The end result is thousands of flood hydrographs ranging in magnitudes from common to extreme. The advantage over event-based simulation approach is that statistical distributions of initial (pre-storm) watershed conditions are likely more realistic since they do not have to be arbitrarily assumed. The advantage over continuous simulation approach is that there is no need to carry out the difficult task of generating thousands of years of continuous synthetic rainfall and temperature sequences of questionable accuracy. Examples of semi-continuous or hybrid stochastic flood models are SEFM (Schaefer and Barker, 2002) and SCHADEX (Paquet et al., 2013).

3.3. MAIN ASPECTS OF STOCHASTIC FLOOD HAZARD MODELLING FOR DAM SAFETY

There are three distinct aspects of stochastic flood simulation for a hydroelectric system consisting of a single or multiple dams and reservoirs.

1. Simulation of natural runoff from the local watershed and inflow into the reservoir.

2. Simulation of reservoir operating rules (if any), i.e. flood routing for a single reservoir or a system of multiple dams and reservoirs.

3. Simulation of on-demand availability of various system components such as failure of different discharge facilities, telemetry errors, human operator errors, or some combination of those.

Ideally, all three aspects are combined within the stochastic simulation framework, and multi- thousand years of extreme storm and flood annual maxima are generated by computer simulation. The simulation for each year contains a set of climatic and storm parameters that are sampled through Monte Carlo procedures based on the historical record and collectively preserved dependencies among different hydrometeorological inputs. Execution of a rainfall- runoff model combined with reservoir routing of the inflow floods through the system and stochastically modelled failure/availability of various system components provides the computation of a corresponding multi-thousand year series of annual flood maxima. Simulated flood characteristics such as peak inflow, maximum reservoir release, inflow volume, and maximum reservoir level are the parameters of interest.

However, it is extremely difficult if not impossible to accurately cover all three aspects of stochastic flood simulation due to the enormous complexity of a dam/reservoir system and all possible interactions among its components. That is why in practical applications not all flood producing factors are modelled to the same extent - some are treated as stochastic variables, and some are fixed or not modelled at all. For instance, the third aspect of flood hazard simulation mentioned above (stochastic simulation of on-demand availability of various system components) is rarely carried out due to complexities and difficulties in describing probability distributions of variables such as spillway gate failure or human error. A recent study by Micovic et al. (2016) attempted to cover all three aspects of stochastic flood hazard simulation on a system of three dams and reservoirs with seasonally fluctuating reservoir levels and active discharge control systems. The aim of the study was to examine how the inclusion of spillway gate failures likelihood functions in the stochastic flood modelling framework affects the probability of dam overtopping. The results indicated that dams are much more likely to be overtopped due to an unusual combination of relatively common individual events than due to a single extreme flood event. The all three aspects of stochastic simulation framework are discussed in the following sections.

3.3.1. Stochastic simulation of reservoir inflows

An example of hydrometeorological inputs to stochastic flood model and the dependencies that exist in the stochastic simulation of a particular input are listed in Table 3.1. Note that natural dependencies are prevalent throughout the collection of hydrometeorological variables. The natural dependencies/correlations are preserved in the sampling procedures with a particular emphasis on seasonal dependencies. For instance, the sampling of freezing levels is conditioned on both month of occurrence and 24-hour precipitation magnitude. The watershed conditions for soil moisture, snowpack, and initial reservoir level are all inter-related and inherently correlated with the magnitude and sequencing of daily, weekly and monthly precipitation. These inter-relationships are established through calibration to historical streamflow records in long-term continuous watershed modelling and the state variables are stored for each day of the calibration period (typically 25-years or more). The inter-dependencies are preserved for each flood simulation through a resampling procedure.

Table 3.1. Hydrometeorological Inputs to SEFM for BC Hydro's Campbell River System

Model input	**Dependencies**	**Probability model**	**Comments**
Storm seasonality	Independent	Normal distribution	End-of-month storm occurrences
72-hour precipitation magnitude	Independent	4-parameter Kappa distribution	Developed from regional precipitation analyses and isopercental spatial storm analyses
Temporal/spatial distribution of storms	Independent	Resampling from equally-likely historical storms	15 prototype storms, 72-hour to 144-hour long time-series
Air temperature and freezing level temporal patterns	Temporal patterns are matched one-to-one to prototype storms	Resampling from historical storms	Pattern indexed to 1,000 mb temperature and freezing level for day of max. 24hr precipitation
Air temperature at 1,000 mb	Storm magnitude	Physically-based stochastic model	For day of maximum 24-hour precipitation in storm
Air temperature lapse-rate	Independent	Normal distribution	For day of maximum 24-hour precipitation in storm
Freezing level	1,000-mb temperature, temperature lapse-rate and storm magnitude	Physically-based stochastic model	For day of maximum 24-hour precipitation in storm

Watershed model antecedent conditions (snowpack, soil moisture)	Seasonality of storm	Resampling of historical conditions Oct 1983 – present	Sampled from antecedent condition files. Sampled year is independent, sampled month corresponds to month sampled from seasonality of storm occurrence.
Initial reservoir level	Seasonality of storm and watershed model antecedent conditions	Resampling of historical conditions with the same reservoir operating rules as the current ones (1998 – now)	Sampled from recorded reservoir level data. Sampled year has similar antecedent precipitation as year sampled for watershed model antecedent conditions.

3.3.1.1. Storm seasonality

The seasonality of storm occurrence is defined by the monthly distribution of the historical occurrences of storms with widespread areal coverage that have occurred over studied area. This information is used to select the date of occurrence of the storm for a given stochastic simulation. The basic concept is that the seasonality characteristics of extraordinary storms used in stochastic flood simulations should be the same as the seasonality of all significant storms in the historical record. The term "significant" is somewhat subjective, but it usually refers to storm events where precipitation maxima for a given storm duration exceeds a 10- year return period at three or more precipitation gauges within the studied area. This criterion assures that only storms with both unusual precipitation amounts and broad areal coverage would be considered in the analysis.

Figure 3.1 shows an example of this procedure applied to the 1,463 km^2 Campbell River watershed on Vancouver Island, BC, Canada and using the 72-hr storm duration. The procedure resulted in identification of 69 significant storms within the 1896-2009 period. A probability- plot was developed using numeric storm dates (9.0 is September 1st, 9.5 is September 15th, 10.0 is October 1st, etc.) and it was determined that the seasonality data could be well described by a Normal distribution. A frequency histogram was then constructed based on the fitted

Normal distribution to depict the twice-monthly distribution of the dates of significant storms for input into a stochastic simulation framework.

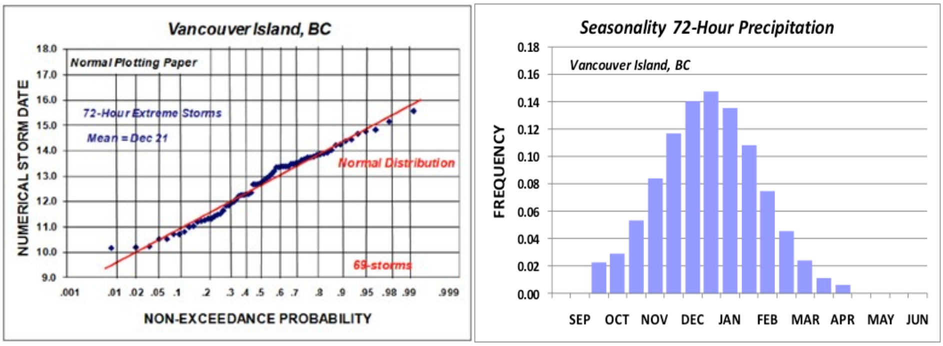

Figure 3.1 Probability plot and frequency histogram of storm seasonality for the Campbell R. watershed in Canada

Figure 3.1 shows that significant historical storms have occurred in the period from early October through about mid-March with a mean date of December 21st. The probability of occurrence of a storm for any given mid-month or end-of-month can be determined from the incremental bi- monthly frequencies depicted in the Figure 3.1 histogram (e.g. zero probability for September mid-month, and probability of 0.0228 for September end-month).

3.3.1.2. Precipitation magnitude-frequency relationship

Generally speaking, floods could result from storms of various durations. This is especially true for very large watersheds (e.g. > 10,000 km^2), where significant floods could originate from intense short-duration storms covering only a part of the watershed, or from a wide-spread general synoptic storm of longer duration that cover the entire watershed area.

The direction of the storm and its speed of movement over the watershed is also an important factor. Consequently, proper stochastic flood modelling process should be sampling rainfall storms of different duration from their respective frequency distributions and weight modelled floods according to the observed frequency of different duration rainfall storms used to produce said floods.

This approach implies the existence of separate rainfall-frequency relationship for all considered storm durations. However, the stochastic modelling is often simplified by choosing so called “critical storm duration” for a particular watershed and deriving a rainfall-frequency relationship only for that duration. This simplification is particularly effective in watersheds with drainage area sizes under approximately 5,000 km^2 where it was relatively easy to determine the typical storm duration from precipitation gauges in the area, and where exclusion of other storm durations in stochastic flood simulation would have relatively minor effect on overall accuracy.

The vast majority of precipitation stations record on a daily basis which results in logical choices of the 1-day, 2-day, 3-day or 4-day duration for the precipitation-frequency analysis. For instance, BC Hydro experience shows that for watersheds in Pacific Coastal zone of British Columbia the 72-hr duration (3-day) is the most representative of the typical storm duration, whereas for some watersheds in Interior British Columbia it is the 48-hr duration. Similarly, Électricité de France generally uses the 3-day duration in their SCHADEX stochastic model for most French watersheds, with some small and flash-flood prone watersheds being treated with shorter storm durations.

The magnitude of precipitation relevant to dam safety analyses is typically several orders of magnitude more extreme than what has been observed in the historic record. As such, the estimation of this range of rainfall presents special difficulties and requires the extrapolation of relatively short historical data records. This extrapolation is challenging, especially considering that rainfall input is generally the most significant contributor to resulting stochastically derived flood hydrographs. There are different ways to do this extrapolation and obtain precipitation magnitude-frequency relationship over the entire probability domain of interest, including return periods of 10,000 years and beyond. A couple of examples are described here:

1. In the SEFM model (Schaefer and Barker, 2002), the precipitation magnitude-frequency analysis is done by utilizing the regional L-moment analysis (Hosking and Wallis, 1997). By employing the regional precipitation-frequency analysis we can compensate for the short length of available hydrometeorological record by considering a larger study area. This approach takes advantage of the situation that the size of the study area is much larger than the typical areal coverage of storms for the duration of interest, and there will be many storms in the regional dataset with return periods higher than indicated by the chronological length of the historical record.

Applying this approach to the Campbell River watershed above Strathcona Dam on Vancouver Island, BC, Canada included assembling storm data from all locations that were climatologically similar to the Campbell River region. Precipitation annual maxima series data were assembled for the critical duration (72-hour in this case) from all stations on Vancouver Island and stations between latitude 47° and 52° N from the Pacific Coast eastward to the crest of the Coastal Mountains (Canada) and Cascade Mountains (USA). This totaled 143 stations and 6,609 station-years of record for stations with 25-years or more of record. The precipitation-frequency relationship (Figure 3.2) was developed through regional L- moment analyses of point precipitation and spatial analyses of historical storms to develop point-to-area relationships and determine basin-average precipitation for the watershed using the 4-parameter Kappa distribution. The uncertainty bounds were developed through Latin-hypercube sampling method (McKay et al., 1979; Wyss and Jorgenson, 1998) where regional L-moment ratios and Kappa distribution parameters were varied to assemble 150 parameter sets and perform Monte Carlo simulation using different probability distributions for individual parameters.

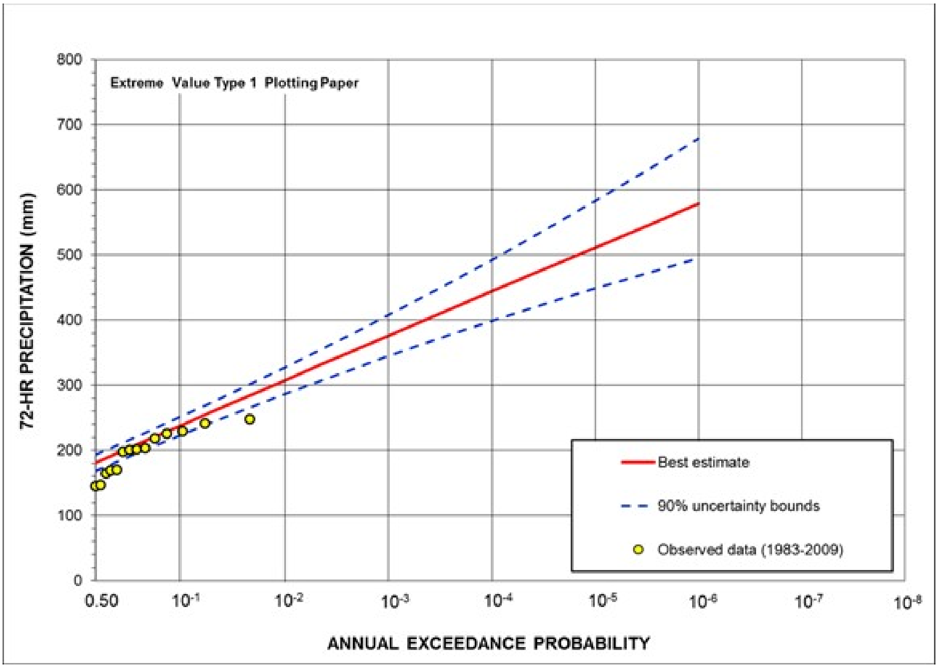

Figure 3.2 Computed 72-hour precipitation-frequency curve and 90% uncertainty bounds for the 1193 km^2 Strathcona Dam watershed

2. In the SCHADEX model (Paquet et al., 2013), the precipitation magnitude-frequency analysis was catchment-specific (a regional approach is used if local data are lacking) utilizing weather patterns classification and Multi-exponential distribution linked to specific weather patterns (Garavaglia et al., 2010). The underlying hypothesis is that a rainfall sampling based on days having similar atmospheric circulation patterns will provide more homogeneous sub-samples which will in turn reduce uncertainty associated with extrapolation of short sample size. The rainfall stochastic generator of SCHADEX is based on the concept of a 3-day event so-called “centered rainfall event”. Therefore, SCHADEX only develops precipitation magnitude-frequency for the central daily rainfall (dark blue in Figure 3.3 below), and precipitation quantiles of the day before and the day after (adjacent rainfalls, light blue in Figure 3.3) are estimated using the probabilities of the ratios “Pa-/Pc” and “Pa+/Pc”, computed from rainfall events identified in the historical record. Note that Pa-, Pc and Pa+ represent daily rainfall amounts for the day before the central day, the central day and the day after the central day, respectively.

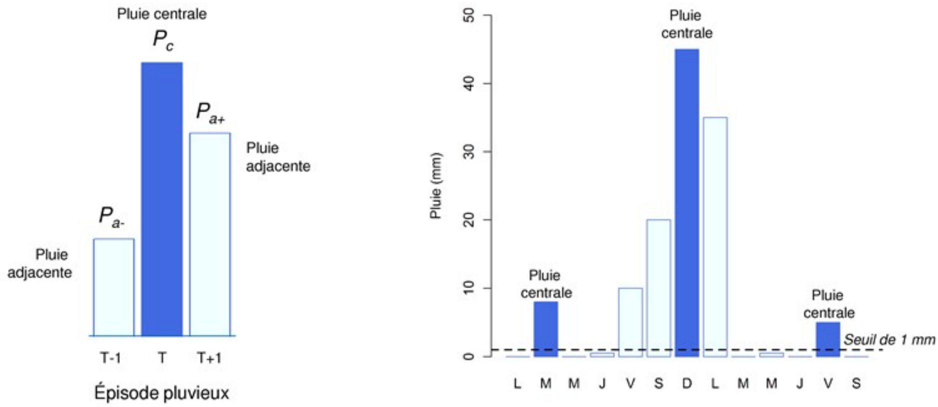

Figure 3.3 SCHADEX concept of centered rainfall event (with central and adjacent rainfalls)

3.3.1.3. Temporal and spatial distribution of storms

The process of stochastic storm generation requires both spatial and temporal storm templates that are scalable. The spatial and temporal storm templates are linearly scaled by the ratio of the desired basin-average precipitation of certain duration to the basin-average precipitation of the same duration observed in a selected storm template (i.e. prototype storm). These storm templates should be prepared from as many historically observed storms as possible in order to capture diversity among storms in terms of spatial and temporal distribution of precipitation. Typically, 10 to 20 storm templates should be enough to capture storm diversity over a given watershed, for watersheds sizes up to about 5,000 km^2. Larger watersheds should be divided into zones of a size suitable for describing the spatial and temporal variability of storm types that may affect the watershed on a given day, with separate storm analyses carried out for each zone within a watershed.

These kinds of decisions are typically site-specific and depend of detailed meteorological analysis of the given area, including use of measurable parameters such as geopotential height contour maps for different pressure heights, precipitable water, convective available potential energy and the scale of the precipitation footprint (synoptic, mesoscale, or local convective storms) determined by the percentage of gauges in the area exceeding a specified daily precipitation threshold. For instance, there could be large areas with fairly simple climatology, whereas some relatively small watersheds could have complex climatology with multiple storm types with different spatial, temporal and seasonal characteristics, resulting in a mixed population of storms and floods.

In the presented example of the 1,463 km^2 Campbell River watershed located in Pacific Coastal zone of British Columbia, as mentioned earlier in Section 3.1.2, it was fairly straightforward to determine the typical storm duration from precipitation gauges in the area, meaning that exclusion of other storm durations/types in stochastic flood simulation would have relatively minor effect on overall accuracy.

Spatial storm templates for a given storm are developed analyzing rainfall data and using GIS analyses to compute basin-average precipitation of certain duration (e.g. 24, 48, 72-hr). The analyzed rainfall data could be hourly or daily as well as from point measurements or from radar, depending on what type of rainfall data is required as an input into a rainfall-runoff model used in stochastic flood simulation. An example of spatial storm template (a 72-hour precipitation for the October 1984 storm over the Strathcona Dam basin) is shown in Figure 3.4.

Temporal storm templates could be developed as a 3-day template with the centered main rainfall and adjacent rainfalls as assumed in SCHADEX methodology and described in the previous section (Figure 3.3). A more elaborate way to develop temporal storm templates is utilized by the SEFM method where hourly rainfall data from many point-measurements station within a given watershed are used to obtain the basin-average rainfall of specified duration (e.g. max.72-hr). This is followed by the examination of the 10-day period of precipitation encompassing the max. 72-hour precipitation using daily synoptic weather maps, radiosonde data and air temperature temporal patterns.

This procedure leads to the identification of the time span during which there was a continuous influx of atmospheric moisture from the same air mass where precipitation was produced under similar synoptic conditions. The identified time span provides the starting and ending times for the precipitation segment that is independent of surrounding precipitation and scalable for stochastic storm generation. An example of this type of temporal storm template is shown in Figure 3.5 which depicts the observed 10-day period of basin-average precipitation for the storm of October 14-23, 2003 for the Strathcona Dam basin, with the portion of the hyetograph (in blue) that was identified as the independent scalable segment of the storm and therefore adopted for use as a prototype storm for stochastic storm generation.

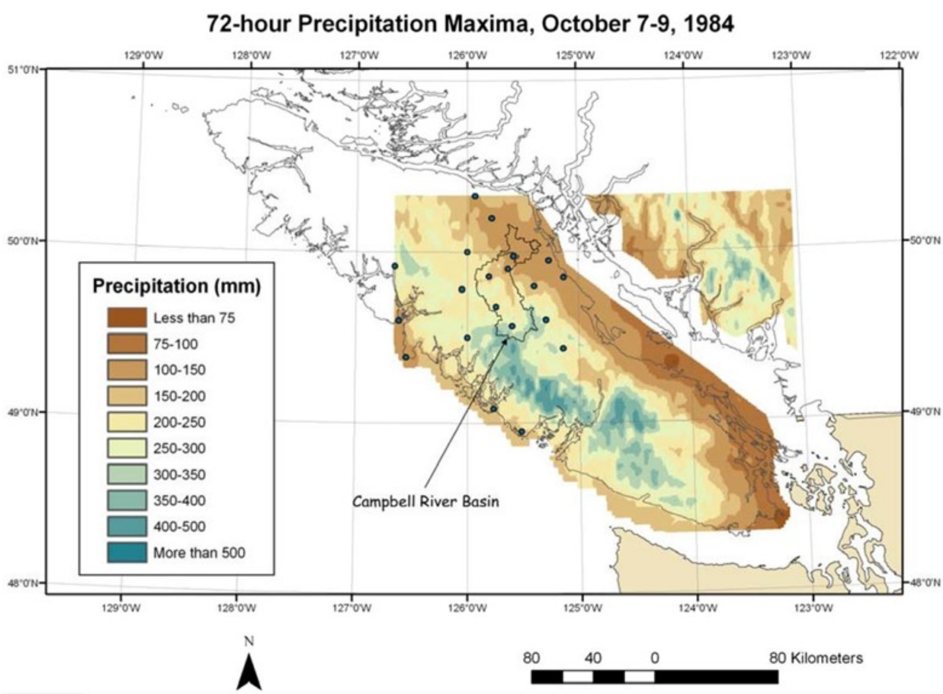

Figure 3.4 Spatial storm template (October 1984 storm)

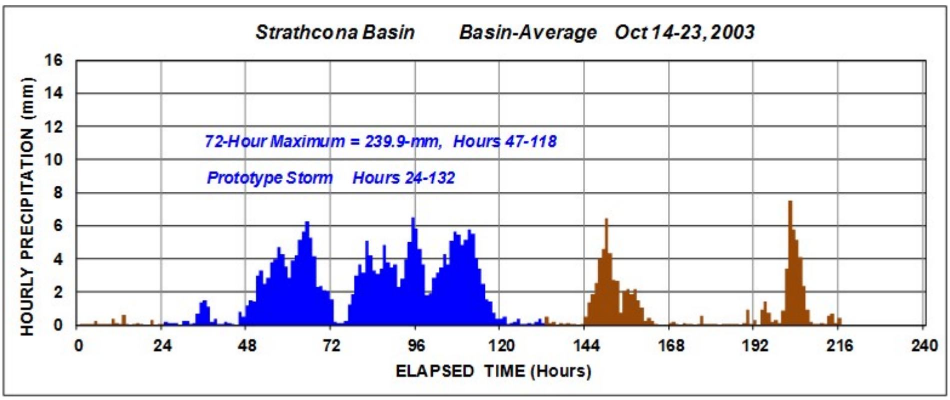

Figure 3.5 Temporal storm template (October 2003 storm)

3.3.1.4. Air temperature and freezing level temporal patterns

The usual approach is to first stochastically simulate 1,000 mb air temperature (i.e. temperature at or near the sea level), followed by stochastic simulation of air temperature lapse-rates that are required for computing both freezing levels and air temperature values within the full elevation range of a given watershed.

Within the stochastic flood simulation framework, 1,000 mb air temperatures during extreme storms could be simulated using a variety of approaches. One example is a physically-based probability model for 1,000 mb dewpoint temperatures derived from monthly maximum dewpoint data (Hansen et al., 1994). This probability model utilizes monthly upper limit dewpoint data and the magnitude of the maximum 24-hour precipitation within the storm relative to 24-hour PMP. The 1,000 mb dewpoint temperatures are drawn from a symmetrical Beta Distribution bounded by lower and upper bounds as shown in Figure 3.6 for December in the Vancouver Island region, BC, Canada. A separate relationship, similar to Figure 3.6, is used for each month because 1,000 mb dewpoint climatology changes with season. Higher maximum 1,000 mb dewpoints are possible in the fall months of October and November than in the colder winter months of January and February, which implies that freezing levels tend to be somewhat lower for storms in the colder winter months.

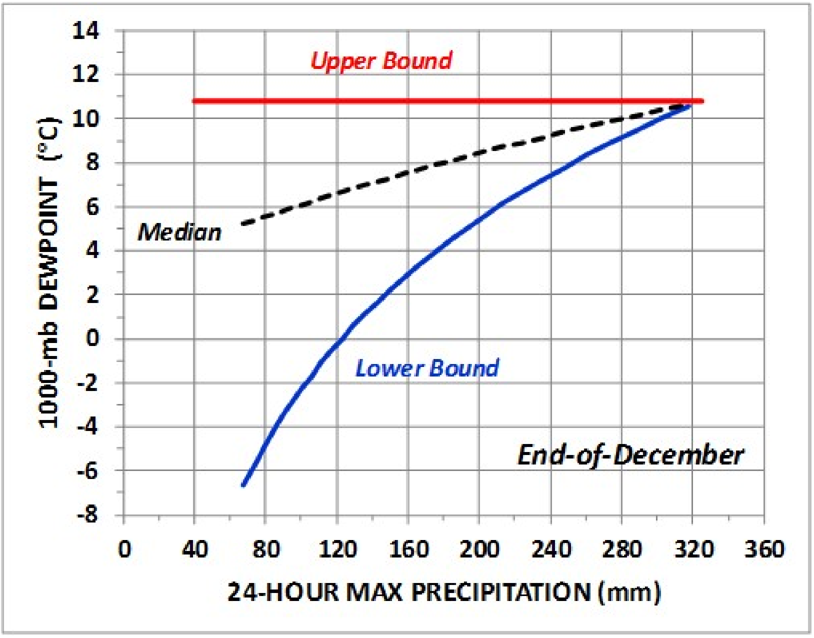

Figure 3.6 Range of 12-hour persisting 1,000 mb dewpoint temperatures utilized by dewpoint temperature probability model (December example)

The next step is to stochastically generate air temperature lapse-rates. For example, analyses of upper air sounding data from Northwestern Washington and Central California stations reveal that air temperature lapse-rates on the day of maximum 24-hour precipitation for noteworthy storms are well described by the Normal Distribution (Figure 3.7). The mean value was found to be 5.1°C/1000 m, which is near the saturated pseudo-adiabatic lapse-rate. Similar results were found if examining the data from Washington or California separately, so the data from the two regions were combined to provide a larger sample for computing the distribution parameters. Stochastically generated 1,000 mb air temperatures and temperature lapse-rate described above are used in computing resulting freezing levels for each storm.

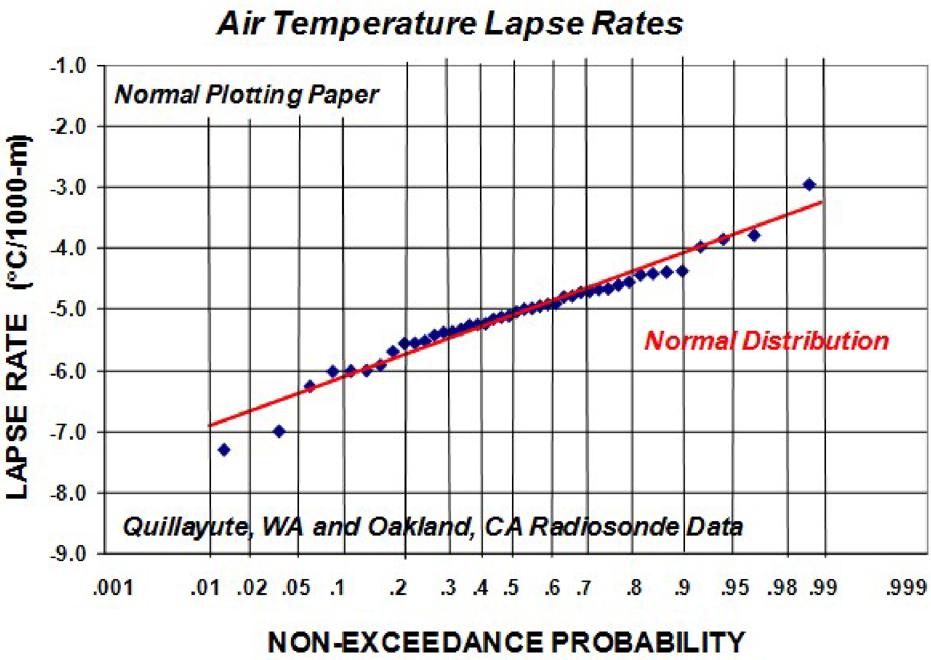

Figure 3.7 Air temperature lapse-rates for day of maximum 24-hour precipitation for storms in Northwestern Washington and Central California

Once air temperatures and freezing levels have been stochastically generated, we could start deriving their temporal patterns that are used in computing snowmelt runoff. Temporal patterns for air temperature and freezing level are matched one-to-one with each prototype storm. These temporal patterns are developed so that they could be rescaled by stochastically drawn values of air temperature and freezing level. Scalable 1,000 mb air temperature and freezing level temporal patterns are constructed by subtracting index values (the highest 6-hour averages observed during the day of maximum 24-hour precipitation) from observed data.

An example of indexed 1,000 mb temperature and freezing level temporal patterns constructed for the Oct. 2003 storm over the Strathcona Dam basin is shown in Figure 3.8. During stochastic flood simulation, index values for 1,000 mb temperature and freezing level are stochastically simulated for each prototype storm and then used to rescale the indexed temporal patterns (e.g. Figure 3.8) by adding the simulated index values. This procedure yields simulated 1,000 mb temperature and freezing level hourly time-series similar to those historically observed and therefore physically plausible.

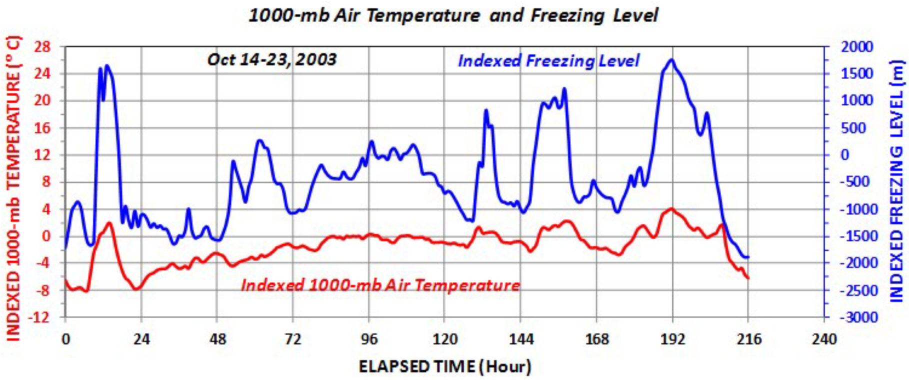

Figure 3.8 Indexed 1,000 mb temperature and freezing level temporal patterns for the Oct. 2003 storm

3.3.1.5. Watershed model antecedent conditions sampling

As mentioned earlier, a continuous watershed model (rainfall-runoff model) is calibrated to realistically simulate hydrological behaviour of the watershed over a continuous period of many years, typically dependent on the availability of climate input data. The model state variables (snowpack accumulation, soil moisture conditions, glacier mass balance, base flow from seasonally-varying aquifer supplies, etc.) are computed continuously by the model over the long simulation period. This creates a continuous database of watershed initial conditions which could be stochastically sampled at any time/season of the year and assumed to occur at the onset of a stochastically generated storm event. Using this approach, we ensure that the full range of synthetic storm events is simulated with the full range of watershed's historically observed internal states (e.g. extreme rainfall on a dry watershed, rain-on-snow events, average rainfall on a saturated watershed, etc.).

3.3.1.6. Initial reservoir level

A resampling approach is typically used to determine the reservoir elevation at the beginning of the stochastic flood simulation. Reservoir operating rules, especially in complex systems of two or more reservoirs usually change over time due to various reasons. Reservoir operating rules represent a compromise among the needs of various stakeholders. As a result, hydropower operation, flood protection, environmental constraints and recreational demands limit the reservoir operating range. It is therefore important to resample reservoir level data only from the period in historic record that reflects current system/reservoir operating rules. This may lead to a fairly short record length for reservoir level data, especially if the changes in reservoir operating rules were implemented relatively recently. In these cases, it may be prudent to use a reservoir simulation model and combine historical inflow data with the new reservoir operating rules, which would yield a longer record of synthetic reservoir levels reflecting the current operation.

3.3.2. Simulation of reservoir operation – flood routing

After thousands (or millions) of inflow hydrographs have been stochastically derived and coupled with initial reservoir levels, they have to be routed through a reservoir to obtain peak reservoir level and outflow hydrographs that enter any downstream reservoir(s). Flood routing simulations are carried out with the aim to realistically capture the way a reservoir (or a system of reservoirs) may be operated during flood events ranging in annual exceedance probabilities from 1/2 to beyond 1/10,000. In reality this is a rather complex decision making process involving various factors such as the inflow forecast, flood magnitude, downstream environmental conditions existing at the time of the inflow, corporate pressures, and other site- specific and season-specific conditions.

Generally speaking, for very large floods the routing procedure becomes fairly simple, because the main goal is to save the dam from overtopping (or if overtopping is tolerable, to prevent the reservoir reaching an elevation that endangers the stability of the dam) and utilize as much discharge capacity as possible (i.e. fully open spillway gates, low level outlet gates, etc.). In such cases the safety of the dam takes precedence over every-day operational constraints such as, for example, downstream discharge limits pertaining to residential flooding, environmental and recreational requirements. Things are more complicated when routing smaller floods (e.g. return periods between 10 and 50 years or so) because there could be ways to safely pass the flood and still satisfy other constraints, especially if the inflow forecast is reasonably reliable.

For example, a dam operator may decide to start spilling moderate amounts of water (within downstream discharge limits) for several days before forecasted inflow arrives so that there is enough storage in the reservoir to absorb the incoming flood while keeping spill below downstream discharge limits. Note that this strategy depends on the accuracy of the inflow forecast and flood magnitude – when flood magnitude exceeds certain level, the flood routing options diminish and the only strategy becomes fully utilizing available discharge facilities and avoid dam overtopping.

The mentioned pre-spilling strategy and a dam operator decision making process could be modelled using the following two-step approach:

1. The first step in flood routing simulations is to route the stochastically-generated inflow hydrographs through the reservoir (or system of reservoirs) using the standard flood routing procedures

2. In the second step, the results from the standard flood routing performed in the first step are treated as a "forecast", and the inflows are then routed using modifications reflecting the pre-spill or any other dam operator’s strategy that deviates from the standard routing procedure. Although the second step is performed with the benefit of complete foresight, the routing modification and the dam operator’s decisions could be developed recognizing that the real inflow forecast is uncertain.

The two-step approach above, when incorporated in stochastic flood simulation, provides an additional “operational” component to the whole process and results in more realistic modelling of small to moderate floods, where there could be some flexibility in the routing procedure.

3.3.3. Stochastic simulation of the availability of discharge facilities

Generally, the reservoir routing of an extreme flood in deterministic dam safety analyses (i.e. the PMF) is performed by assuming a conservatively high initial reservoir level typically combined with the assumption that all spillway gates open as required to pass flood discharge. Some analyses assume the “n-i” rule where “n” is the number of spillway gates and “i” is the number of spillway gates assumed unavailable. However, depending on values for “n” and “i”, this approach may be too conservative for some spillway configurations.

During the passage of a flood, one or more of spillway gates may be unavailable for various reasons including debris jams, human error and mechanical or electrical malfunctions. Due to numerous interconnected components of a spillway gate system and consequently the infinite number of reasons for failure, it is impossible to directly compute the probability of gate failure on demand. This probability has to be estimated through some kind of analysis which should include as many failure modes as possible, with consideration of site-specific knowledge of the state of various gate system components as well as frequency and thoroughness of gate testing.

One example of such analysis was carried out during gate reliability assessments of five US Army Corps of Engineers Huntington District dams (Lewin et al., 2003). Gate and equipment testing for these five dams of 3-4 times per year was considered relatively infrequent. In addition, many components, such as relays or limit switches were tested only when the gate test used those particular components. During 18 gate tests, there were three instances when a gate failed to operate correctly. A fault tree analysis of gate failure modes indicated that for a gate opening in ideal conditions, similar to those under which gate tests were carried out, a probability of failure on demand was assessed to be of the order of 1 in 10. The probability of multiple failures of gates during an extreme flood was estimated to be at least 1 in 100 per demand due to a common cause failure regardless of the number of gates in an installation.

The availability of powerhouse discharge during flood is also uncertain. Flood-inducing rainfall could be very severe and could conceivably cause erosion or landslides that might result in transmission line failures, making generation impossible. Severe rainfall could also cause other powerhouse-disabling damage such as powerhouse flooding or penstock damage. Perhaps the most realistic way of simulation would be to somehow tie the availability of the powerhouse to the storm magnitude (e.g. if the simulated 72-hour basin-average precipitation has the annual exceedance probability of 1/1,000 and greater, the powerhouse discharge is disabled).

The importance of spillway gate reliability could be very high and typically increases as the size of reservoir surcharge storage decreases. For example, Micovic et al. (2016) showed that for a dam with very small reservoir surcharge storage, simulating possibility of random spillway gate failures during the flood increased the resulting annual probability of dam overtopping by five orders of magnitude over the case in which all spillway gates are assumed operable.

3.3.4. Simulation procedure

An example schematic of stochastic flood simulation involving the steps described in Section 3 of this chapter is shown in Figure 3.9. Precipitation to runoff conversion in this example was done by the UBC Watershed Model (Quick, 1995; Micovic and Quick, 2009).

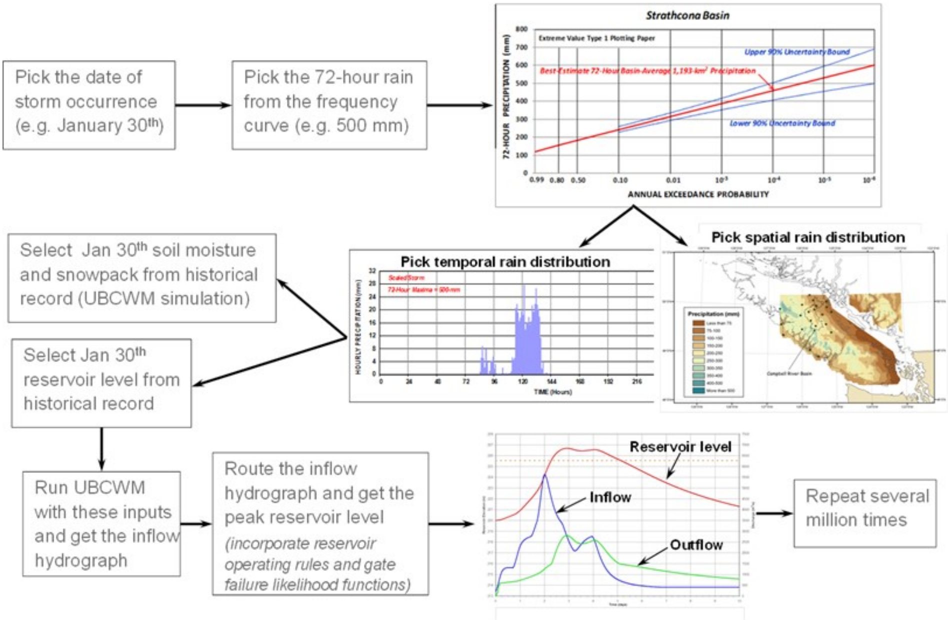

Figure 3.9 Stochastic flood simulation flow chart for the 1193 km^2 Strathcona Dam watershed in British Columbia, Canada

3.4. ESTIMATING UNCERTAINTY IN STOCHASTIC FLOOD MODELLING

Stochastic flood modeling is technically sound in its principle since it attempts to derive probabilities of extreme floods from the physically plausible modelling framework (considering the available historical data and state-of-art hydrometeorological modelling tools). However it should be stated that it is impossible to estimate with certainty the upper tail of statistical distribution for a flood parameter such as peak inflow or peak reservoir level. In his review of BC Hydro's Mica Dam stochastic flood modelling Vit Klemes (2000) stated that:

"... the factual necessary information (data + knowledge of the processes involved) to which these technologies could be applied simply does not exist and it cannot be manufactured just because it is needed for risk analysis. In this sense the uncertainties are irreducible and the best we can hope for is to arrive at their rough quantitative estimates and, based on them, to outline plausible credibility windows or bands ..."

In general, a calibrated watershed model and hydrometeorological inputs developed from historical data represent one plausible description of the "true state of nature" for the behavior of a watershed. It must be recognized that uncertainties exist in the estimation of hydrometeorological inputs and watershed model parameters due to both aleatoric and epistemic reasons. Consequently, there are many alternative combinations of probabilistic and deterministic models and model parameters that could plausibly describe the “true state of nature”. For instance, the extrapolation of plausible weather patterns is based on historical precedent. Therefore, the potential for future climate change is one of the uncertainties in this approach that needs to be handled via adoption of an appropriate level of conservatism in selection of design parameters, combined with a thorough uncertainty analysis. The goal of the uncertainty analysis is to derive a mean-frequency curve and uncertainty bounds for the various flood characteristics in a manner that reasonably captures the current understanding of the hydrologic behavior of the watershed as well as the effect of uncertainties in estimating the flood-frequency characteristics.

Considering physical complexity and number of parameters involved in the process of flood simulation and routing through a system of dams and reservoirs, it is practically impossible to accurately quantify associated uncertainties. It is therefore prudent to use a parsimonious approach in the selection of hydrometeorological inputs and watershed model parameters to be included in the uncertainty analysis. This generally requires using a two-step approach:

- Step 1 involves sensitivity analyses (and some engineering judgement) to determine which hydrometeorological inputs and model parameters have the greatest effect on the magnitude of the flood outputs of interest for a particular dam or system of dams.

- In step 2, the uncertainty analysis is performed on the inputs/parameters identified in Step 1.

3.4.1. Sensitivity analyses

Global Sensitivity Analysis (Saltelli et al., 2001) is recommended for use with stochastic flood modeling applications, as with any other applications utilizing Monte Carlo sampling approaches. This kind of sensitivity analysis is capable of examining sensitivity with regard to the full range of parameter distribution. As such, Global Sensitivity Analysis can measure the effect of interactions between parameters and handle non-linear behavior. In contrast, Local Sensitivity Analysis (e.g. “one-at-a-time” sampling) examines sensitivity only with regard to point estimates of parameter values, which results in the sensitivity measure being affected by the choice of parameter values.

Figure 3.10 depicts examples of the type of scatterplots produced from the Monte Carlo simulations that were used to assess the sensitivity of the peak hourly reservoir inflow to hydrometeorological inputs such as freezing level (i.e. the altitude above which precipitation is not liquid) and temporal distribution of storm precipitation.

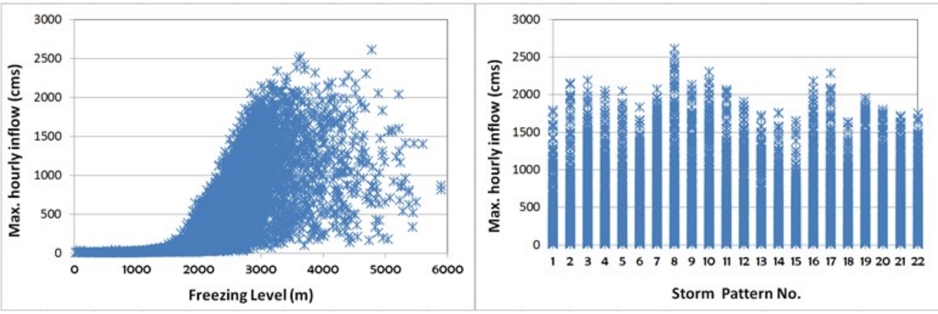

Figure 3.10 Scatterplot showing moderate to high sensitivity of peak reservoir inflow to freezing level and storm temporal distribution for the La Joie Dam watershed in Canada

Similar scatterplots are produced for all flood characteristics (inflow, outflow, reservoir level) and all relevant hydrometeorological inputs and rainfall-runoff model parameters; those exhibiting both high sensitivity and high level of uncertainty in parameter estimation are typically selected to be included in the uncertainty analysis. An example of this procedure as applied to the 1,000 km^2 La Joie Dam watershed in British Columbia, Canada is presented in Table 3.2, which shows a qualitative listing of the sensitivity of the peak reservoir level to the various hydrometeorological inputs and watershed model components/parameters. Table 3.2 also contains a qualitative assessment of the relative magnitude of uncertainties for those inputs/parameters.

Table 3.2 Qualitative sensitivity of the La Joie Dam maximum reservoir level to various hydrometeorological inputs and watershed model parameters

Model component	Sensitivity to model component	Magnitude of uncertainty	Comments
Storm seasonality	Moderate	Moderate	Large sample set of storms Greater uncertainty for early-season storms
48-hour basin-average precipitation-frequency relationship for watershed	High	Moderate to high	Large sample of annual maxima Uncertainty highest for extreme events
Temporal and spatial distribution of storms	High	Low to moderate	Diverse sample of spatial/temporal patterns for 22 prototype storms
Antecedent precipitation	Moderate	Low	Adequate sample of historical antecedent precipitation

Antecedent soil moisture conditions	Moderate	Low	Adequate sample of historical antecedent soil moisture conditions
Baseflow	Low	Low	Adequate sample of historical baseflow conditions
1,000 mb air temperature	Moderate	Low to moderate	Utilized in computing freezing level
Freezing level	Moderate to high	Moderate	Runoff volume is sensitive to freezing level in winter months
Rainfall-runoff modeling	Moderate	Low to moderate	Long record of historical flows for watershed model calibration
Snowmelt runoff modeling	Moderate	Low to moderate	Long record of historical flows for watershed model calibration
Watershed response to fast runoff	Moderate	Moderate to high	Long record of historical flows for watershed model calibration Uncertainty in response timing
Computation of peak reservoir level via spillway stage-discharge curve	Low to moderate	Low to moderate	Stage-discharge curves are typically based on field testing and hydraulic model results

The relative rankings in Table 3.2 were reviewed and candidates for inclusion in the uncertainty analysis were identified as those inputs/parameters where there was both moderate to high sensitivity and where there was a higher level of uncertainty in estimation of the input/parameter. This assessment resulted in identification of five components of the stochastic modelling framework to be included in the uncertainty analysis for the La Joie Dam watershed as shown in Table 3.3.

Table 3.3 Five model components selected for inclusion in the uncertainty analysis for derivation of flood frequency curves and uncertainty bounds for the La Joie Dam watershed

Model component	**Anticipated contribution to total uncertainty**	**Comments**

48-hour basin-average precipitation-frequency relationship for watershed	High	Uncertainty highest for extreme events
Watershed response to fast runoff (watershed model timing parameter)	Moderate to high	Affects magnitude and timing of reservoir inflow flood peak
1,000 mb air temperature	Moderate	Components for computing air temperature and freezing level hourly time-series during storms. They affect snowmelt runoff particularly at high elevations.
Freezing level	Moderate	
Storm seasonality	Moderate	Uncertainty for months where precipitation magnitudes are unrestricted

3.4.2. *Uncertainty analyses*

The first task in the process of uncertainty analysis is to identify sources of uncertainty and how they can be characterized in the analysis. The process of characterizing the various sources of uncertainty is best done in a team environment where interaction of perspectives increases the understanding of the flood behavior and facilitates identifying the most significant sources for a particular watershed. It is important to distinguish between two main categories of uncertainty:

- Aleatoric uncertainty is irreducible and associated with natural variability of all flood producing factors including both atmospheric processes and watershed hydrological response. For example, flood magnitude at a given watershed at a specific time of year will vary not only due to atmospheric inputs (rainfall and snowmelt) but also due to the chance occurrence of prior climatic conditions and soil properties that led to soil moisture saturation level being what it was at the time of flood. Values of flood producing factors are subject to chance and the primary purpose (and greatest value) of stochastic flood modeling is in addressing the aleatoric uncertainties associated with the hydrometeorological inputs by treating those inputs as stochastic variables instead of fixed values.

- Epistemic uncertainty is associated with our lack of knowledge about a particular variable or process and it may be reduced by a combination of research and additional data acquisition. Some typical sources of epistemic uncertainty in the flood modelling include: rainfall-runoff model parameter uncertainty due to incomplete understanding of the underlying physics of watershed hydrological response; measurement errors in representation of watershed physical features; selection of inappropriate theoretical probability distribution for describing meteorological inputs (e.g. rainfall); uncertainties in reservoir storage-elevation curve or spillway discharge rating curve used in flood routing.

The aim of the uncertainty analysis employing the Monte Carlo procedures is to derive a sample set of flood-frequency relationships for flood characteristics of interest by considering a sample set of "plausible model configurations". In this context, the term "plausible model configurations" represents alternative combinations of hydrometeorological inputs and alternative watershed model parameters that could reasonably describe the "true state of nature" and are selected from the global sensitivity analysis. All of the alternative combination of hydrometeorological inputs and model parameters are "plausible" within the limits of sampling variability of historical data, state-of-knowledge of the hydrologic/hydraulic processes and flood modeling experience/judgment of the analysts.

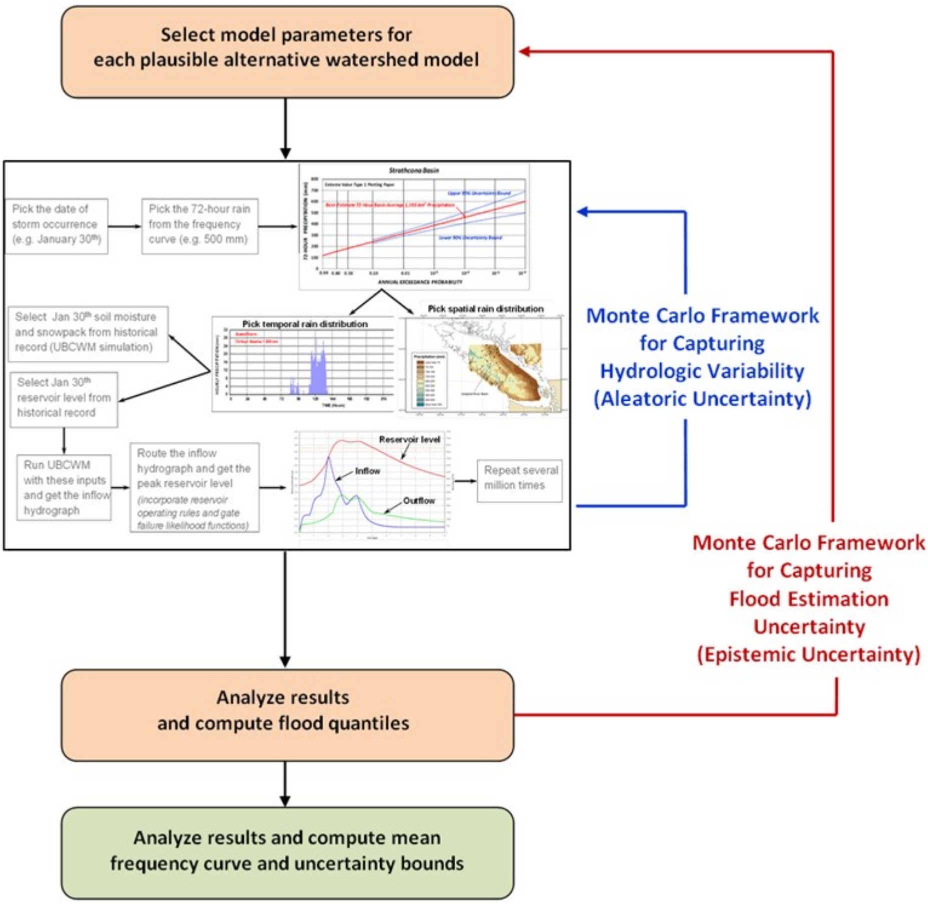

Figure 3.11 Flowchart for Monte Carlo frameworks for stochastic flood analysis and uncertainty analysis

The flowchart in Figure 3.11 describes the process of conducting an uncertainty analysis using a Monte Carlo framework and is based on the concept presented by Nathan and Weinmann (2004). The inner loop is used to derive a flood-frequency relationship for flood characteristics for a given set of models/sub-models and model parameters and explicitly incorporates aleatoric uncertainty. The outer loop represents alternative combinations of models/sub- models and model parameters (alternative configurations) and represents epistemic uncertainty in development of alternative plausible flood-frequency relationships for flood characteristics.

A number of alternative combinations of models/sub-models and model parameters could be assembled using sampling methodology (e.g. Latin-hypercube) to create a sample set of "plausible model configurations" representing reality. This sets the number of repetitions for the outer loop in Figure 3.11. Typically 10-20 alternative model configurations are adequate to reasonably determine the mean flood-frequency relationship for flood characteristics and to characterize the magnitude of the uncertainty bounds. One practical option is to assemble 11 alternative model configurations because the mean frequency curve and uncertainty bounds are often computed in a non-parametric manner by simple ranking of flood outputs for specific AEPs from the group of alternative model configurations. Using the Cunnane's (1978) non-parametric plotting-position formula would result in 95th and 5th percentile flood outputs (e.g. peak reservoir level) being the highest and lowest reservoir levels generated from the 11 model configurations, respectively. Similarly, the median value would be the 6th largest value and the mean value would be computed from the 11 reservoir levels generated for a specific AEP.

A variation of this approach could be to combine all estimates into one, therefore building a kind of predictive distribution. This would be particularly useful in regulatory contexts and jurisdictions in which no mention is made of confidence intervals (e.g. France), and where dam safety assessments are based on a single value corresponding to a specific AEP (currently 10^{-3} or 10^{-4}).

3.4.3. Characterization of uncertainties for selected model components

Characterizations of uncertainties for each of the five selected model components included in the uncertainty analysis of the La Joie Dam stochastic flood modelling example (Table 3.3) are described in the following sections.

3.4.3.1. The 48-hour basin-average precipitation-frequency relationship for watershed

The magnitude of precipitation relevant to dam safety analyses is typically several orders of magnitude more extreme than what has been observed in the historic record. As such, the estimation of this range of rainfall presents special difficulties and requires the extrapolation of relatively short historical data records. This extrapolation is challenging, especially considering that rainfall input is generally the most significant contributor to resulting stochastically derived flood hydrographs.

Due to hydrometeorological homogeneity, the 1,000 km^2 La Joie Dam watershed was coupled together with the adjacent 2,710 km^2 Terzaghi Dam watershed, forming the 3,710 km^2 Bridge River basin for which the basin-average precipitation-frequency relationship was developed. Precipitation annual maxima series data were assembled for the critical storm duration (48-hours in the case of Bridge River basin) from all stations within and near the watershed. This totaled 178 stations and 7,589 station-years of record for stations with 15 or more years of record.

The precipitation-frequency relationships for the Bridge watershed was developed through regional L-moment analyses of point precipitation and spatial analyses of historical storms to develop point-to-area relationships and determine basin-average precipitation for the watershed using the 4-parameter Kappa distribution, which provided the best fit to the observed data sample. Two stations (Downton Lake and Bralorne Upper) from within the Bridge basin were chosen as explanatory stations for the 48-hours basin-average precipitation-frequency relationship. A multiple-regression relationship was developed between the 48-hours precipitation maxima observed at explanatory meteorological stations and maximum 48-hours basin-average precipitation for the Bridge River watershed observed in the 22 historical storms (Figure 3.12). Monte Carlo methods were used to generate 48-hours precipitation-frequency relationships for the watershed accounting for sampling variability and uncertainties in estimation of the various parameters employed in the computation (Figure 3.13). This approach addressed the following sources of uncertainty associated with development of the watershed precipitation-frequency relationship:

- Estimate of mean for point precipitation used in regression,
- Regional L-Cv,
- Regional L-Skewness,
- Regional probability distribution,
- Point to area regression

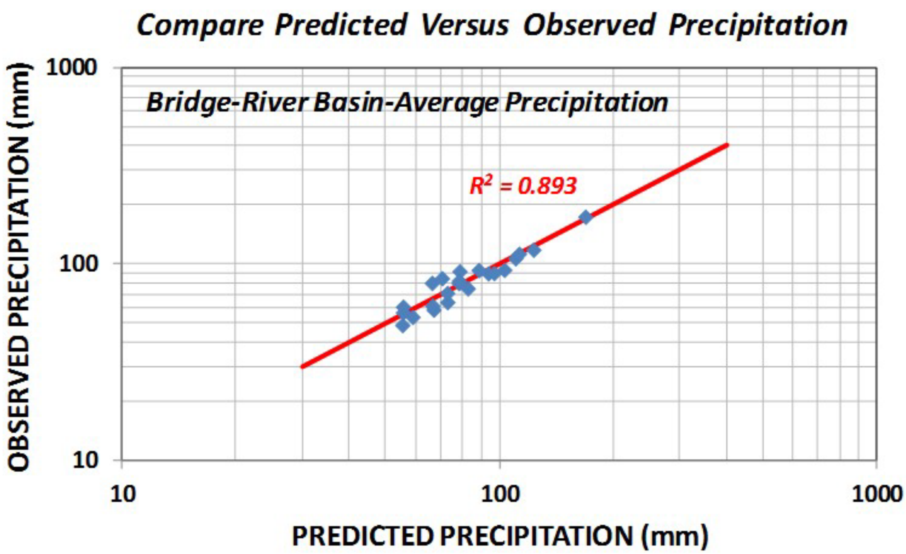

Figure 3.12. Comparison of predicted and measured 48-hours basin-average precipitation for Bridge River watershed based on multiple-regression prediction equation

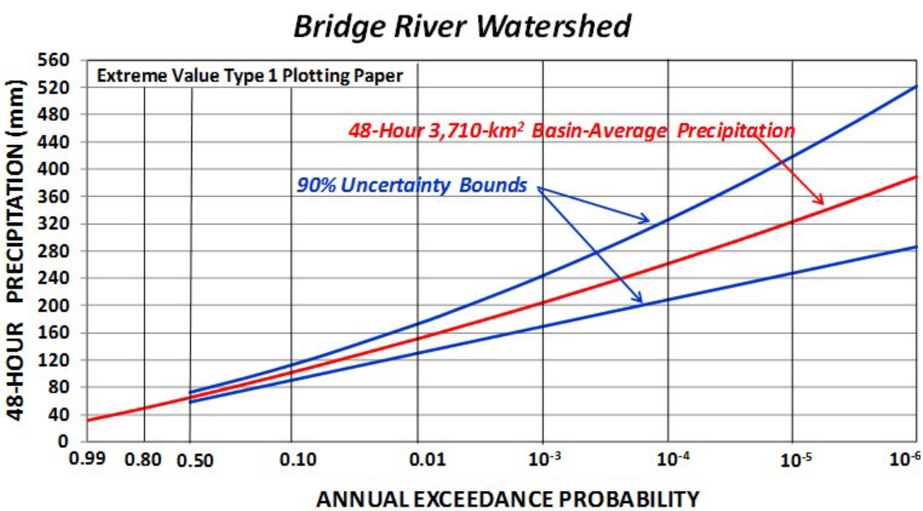

Figure 3.13. Computed 48-hour precipitation-frequency relationship and 90% uncertainty bounds for the Bridge River basin

3.4.3.2. Watershed response to fast runoff

Empirical likelihood functions were developed for the Fast Runoff Timing Constant (FRTK) parameter within the UBC Watershed Model to characterize uncertainties in estimation of parameter values for modelled Bridge River watersheds. The FRTK parameter controls the timing of the watershed response to fast runoff generation and affects the magnitude and timing of the flood hydrograph peak. The best-estimate values for FRTK were determined through calibration of the watershed model to long-term streamflow time-series and to historical floods. The shapes of the likelihood functions were based on experience gained from modelling and calibration of the UBC Watershed Model at basins throughout the world that were hydrologically similar to the Bridge River watershed. Figure 3.14 shows the developed likelihood functions for both Bridge River sub-basins (La Joie and Terzaghi). The summary statistics for these likelihood functions (in days) were:

- 0.5 for the mode/best estimate;
- 0.736 for the mean; and
- 0.357 for the standard deviation.

From these summary statistics, eleven values were selected for each watershed using Latin- hypercube sampling methods.

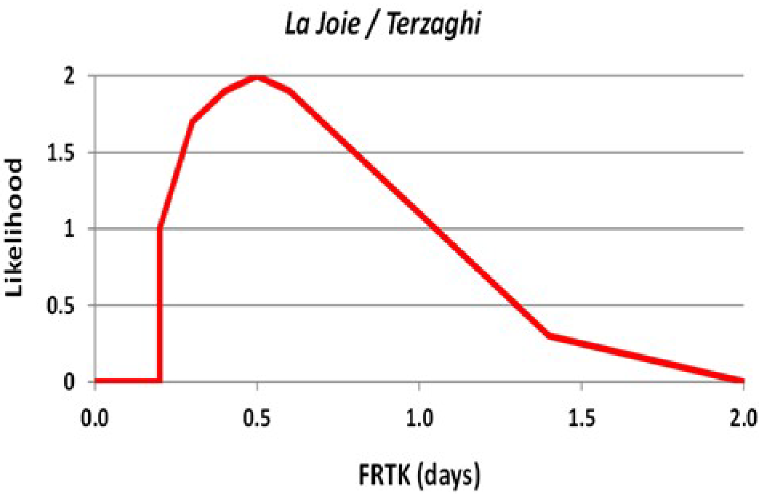

Figure 3.14 Likelihood functions for fast runoff timing constant for Bridge River watersheds

3.4.3.3. The 1,000 mb air temperature and freezing level

Uncertainties in the freezing level for a given stochastic storm simulation were modelled through adjustment of the indexing value of the 1,000 mb air temperature. This approach results in adjustment of the indexing value for the freezing level and for setting the maximum freezing level for a given month. The value of the 1,000 mb air temperature adjustment was found to be 1.3°C through calibration to the historical flood-frequency relationship at La Joie watershed, which is the highest-elevation watershed in the Bridge System with the highest snowmelt runoff contribution.

This calibration should always be carried out as part of the stochastic flood simulation process to ensure that the flood-frequency characteristics predicted by a stochastic model (SEFM in this case) were consistent with the behavior of historically observed flood volumes. Observed reservoir inflow data for La Joie was available for the 1961-2010 period (50 years). Annual maxima 3-day inflow volumes were computed for the period of record and exceedance probabilities determined using a plotting position approach. The 3-day annual maxima were scaled by 1.03 (standard adjustment for 3-day to 72-hour conversion) for comparison with the 72 hour runoff volumes produced by SEFM. The 72-hour duration was chosen to capture the peak runoff from a wide range of storm durations including some of the storm templates that exceeded the 48-hour critical duration discussed in Section 3.4.3.1.

During the calibration, SEFM model parameters had to be adjusted to achieve good match with the historically observed reservoir inflows. In the La Joie case, only the 1,000 mb temperature (generated by a physically-based stochastic model described in Section 3.3.1.5) needed to be adjusted upward by 1.3°C; a minor adjustment and well within the uncertainty of parameter estimation. After model calibration was completed, the 72-hour runoff volumes from the SEFM simulations closely matched the GEV frequency curve based on the observed data to the 500-year return period (Figure 3.15). Differences between simulated and recorded flood-frequency values for floods larger than the 25-year return period are the result of sampling variability in the stochastic model.

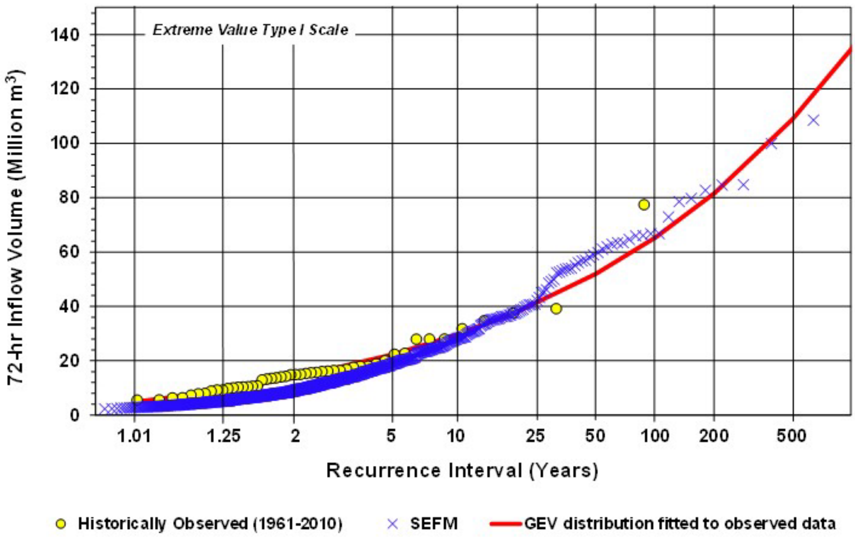

Figure 3.15 La Joie reservoir 72-hour inflow magnitude-frequency calibration (SEFM and observed inflow)

Uncertainty in the 1,000 mb temperature adjustment was characterized °as being equally-likely over a range of +/- 2.0°C centered on the calibration value of 1.3°C. Table 3.4 lists the eleven pairings of 1,000 mb air temperature adjustment and maximum freezing level for the cool season (November to April).

Table 3.4 Uncertainty characteristics for sample set of eleven freezing level parameters for Bridge River watersheds

Sample set	1,000 mb temperature adjustment (°C)	Freezing level adjustment (m)	**Maximum freezing level (m)**					
			Nov	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**
1	-0.7	0	2,700	2,300	2,100	2,100	2,200	2,600
2	-0.3	0	2,800	2,400	2,200	2,200	2,300	2,800
3	0.1	0	3,000	2,500	2,300	2,300	2,400	2,900
4	0.5	0	3,100	2,600	2,500	2,400	2,500	3,000
5	0.9	0	3,200	2,800	2,600	2,500	2,600	3,200
6	1.3	0	3,400	2,900	2,700	2,700	2,800	3,300
7	1.7	0	3,500	3,000	2,800	2,800	2,900	3,500
8	2.1	0	3,700	3,200	3,000	2,900	3,000	3,600
9	2.5	0	3,800	3,300	3,100	3,100	3,200	3,800
10	2.9	0	4,000	3,500	3,300	3,200	3,300	3,900
11	3.3	0	4,200	3,600	3,400	3,400	3,500	4,100

3.4.3.4. Storm seasonality where precipitation magnitudes are unrestricted

Precipitation magnitudes in stochastic flood simulations typically do not have an upper limit. However, restrictions could be placed within the stochastic flood modelling framework on the months where precipitation magnitudes may exceed the Probable Maximum Precipitation (PMP) estimate. In general, precipitation magnitudes are allowed to exceed PMP estimates only in those months occupying the central body of the storm seasonality. This period varies depending on regional climatology and stretches from October to mid-March for the Campbell River watershed (Figure 3.1), but is somewhat shorter (October through February) for the Bridge River region. In those months that are external to the central body of the seasonality data, restrictions are placed on precipitation magnitudes and the upper limit to precipitation is set at the PMP estimate (Micovic et al., 2015) for a particular month.

There is uncertainty in the seasonality of long-duration storms with regard to the months where precipitation magnitudes should be unrestricted. This uncertainty was modeled by considering precipitation magnitudes to be unrestricted for the central body of the seasonality distribution and then extending outwards to consider additional months as unrestricted. Eleven sample sets for storm seasonality were created (Table 3.5) where several monthly groupings were applicable to several sample sets. In particular, the monthly groupings for sample sets 4, 5, 6 and 7 and the percent PMP restrictions generally correspond to the Bridge River region’s climatology.

Table 3.5 Restrictions on 48-hour basin-average precipitation expressed as percentage of PMP

Monthly values of maximum 48-hour precipitation expressed as percentage of PMP										
Sample set	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr
1	U	U	U	U	U	U	U	U	U	U
2, 10, 11	75%	U	U	U	U	U	U	U	U	U
3, 8, 9	52%	75%	U	U	U	U	U	U	U	75%
4, 5, 6, 7	52%	53%	77%	U	U	U	U	U	77%	54%

Note: ”U” corresponds to precipitation magnitudes being unrestricted

3.5. STOCHASTICALLY DERIVED FLOOD FREQUENCY RESULTS WITH UNCERTAINTY BOUNDS

Monte Carlo computer simulations were used to develop magnitude-frequency relationships for maxima of reservoir inflow, outflow, and reservoir elevation for individual dams or for a series of dams within a hydroelectric system. For the examples presented in this chapter (Campbell River and Bridge River hydroelectric systems), these relationships were based on 10,000 computer simulations for each of the eleven "plausible model configurations". This approach is based on the total probability computation procedure developed by Nathan and Weinmann (2001) which greatly reduces the number of simulations that would otherwise have been required to develop the flood-frequency relationships. In particular, it should be noted that each of the eleven "plausible model configurations" was comprised of a random combination of the parameter values for the eleven sample sets, per standard Latin-hypercube methodology.

Flood outputs of interest from the stochastic flood model were presented as probability-plots developed using a non-parametric plotting position. This approach avoids the problems often encountered in selecting and fitting a probability distribution, particularly for flood outputs such as reservoir levels that have been greatly affected by anthropogenic factors such as imposed reservoir operating procedures.

Each of the eleven plausible model configurations produces one flood-frequency relationship for a flood characteristic of interest. For example, Figure 3.16 depicts the eleven flood-frequency relationships for the peak reservoir inflow for the 1,000 km^2 La Joie Dam watershed in British Columbia computed using the stochastic flood model. The mean flood-frequency curves and uncertainty bounds for the peak reservoir inflow for and peak reservoir elevation for the same dam are shown in Figures 3.17 and 3.18, respectively. Note that Figure 3.18 is particularly important in terms of dam safety considerations and decisions because it provides information on the probability of dam overtopping.

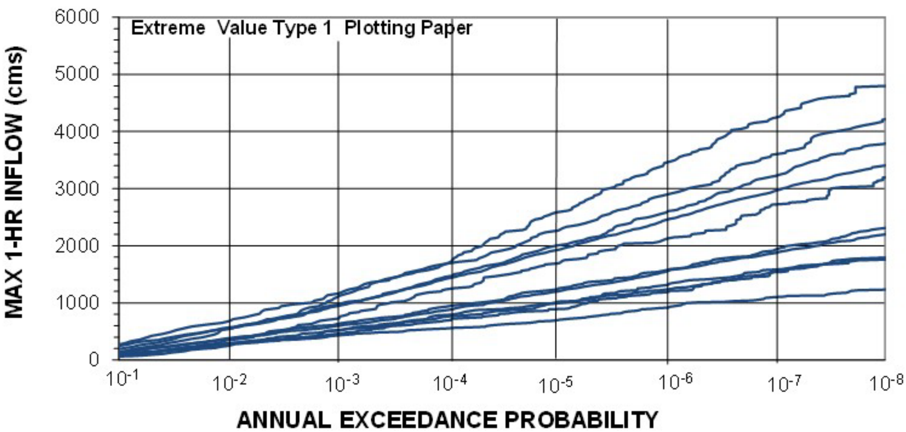

Figure 3.16 Example of simulated flood-frequency relationships for peak hourly reservoir inflow at La Joie Dam for eleven plausible model configurations

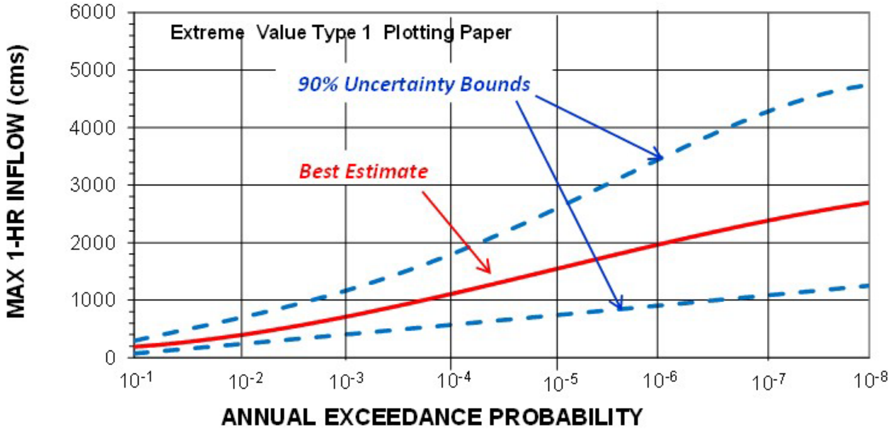

Figure 3.17 La Joie Dam – Frequency curve for peak hourly reservoir inflow simulated by stochastic flood model

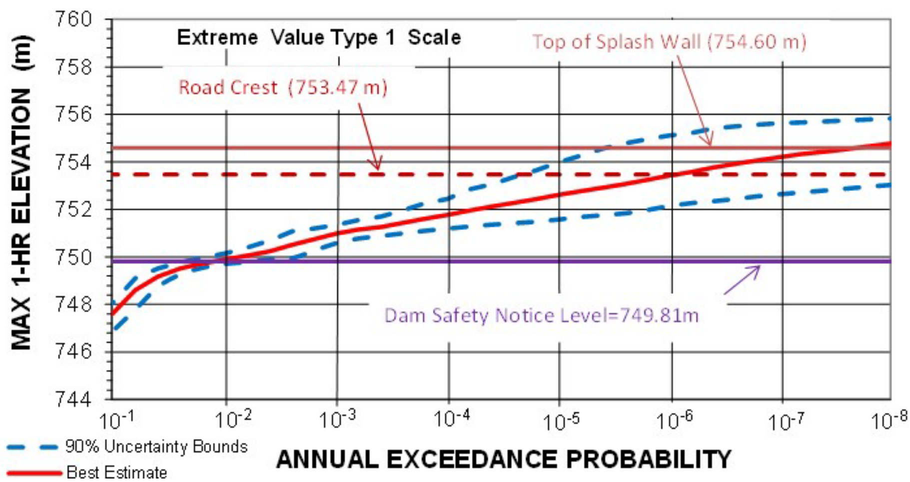

Figure 3.18 La Joie Dam – Frequency curve for peak hourly reservoir level simulated by stochastic flood model

3.6. CONCLUDING REMARKS

Stochastic flood simulation for dam safety is a multi-disciplinary analysis aiming to realistically capture interactions among components of an extremely complex system, considering both natural and anthropogenic inputs. It requires technical expertise in several fields such as meteorology, hydrological modelling and sophisticated statistical analyses, as well as significant amount of hydrometeorological data. Consequently, it is relatively expensive and currently carried out only by a limited number of dam owners in several countries. Also, the considerable data requirements prevent applying this approach in many developing countries at the present time – however that is likely to change in future with continuous increase in computing power and advancements in both remote sensing and data acquisition technologies.

As mentioned earlier, the stochastic simulation approach to flood hazard yields the full continuous probability distributions of reservoir elevation which could then be used to evaluate annual exceedance probabilities of various reservoir levels including the level corresponding to the dam crest (dam overtopping level) as well as the level resulting from the PMF. The approach is recommended for risk assessment studies associated with high hazard/high consequence dams (or a national system of flood protection dykes like in the Netherlands) where potential costs associated with various risk reduction measures are several orders of magnitude higher than the cost of a stochastic flood simulation study.

Conversely, the highest standard-based criterion for dam safety is the PMF which is typically based on the Probable Maximum Precipitation (PMP). In theory, both the PMP and the PMF represent notional upper limits of rainfall and flood magnitude, respectively, and there is zero chance of them being exceeded. In reality, they change over time as new data and methodologies become available, as well as depending on approaches and level of subjective judgement different analysts use in deriving the estimates.

Micovic et al. (2015) analyzed the main meteorological components of a PMP and demonstrated that the uncertainty associated with final PMP estimates (and corresponding PMF results) can be very high, implying that the PMP and the PMF are not true physical limits but simply convenient engineering concepts. Thus, a dam owner using the PMF standard for dam safety may wonder what happens if the current PMF changes or how much larger (or smaller) it could be. Or, what are the risk levels associated with different PMFs as well as the costs of potential risk reduction measures.

These dilemmas could be illustrated by the example of the Cherry Creek Dam in USA, described in Downton et al. (2005). In 1995, the 24-hr PMP for the watershed was estimated by the U.S. National Weather Service to be 536 mm. The U.S. Army Corps of Engineers (USACE) then used this PMP to derive the PMF and concluded that the dam could safely control only 75% of the PMF. Consequently, USACE informed the public that the dam was unsafe and proposed several alternative improvements to the dam, reservoir, and basin, costing up to $250 million. In 2000, the PMP study was carried out by another analyst who came up with the lower 24-hr PMP value of 401 mm (i.e. about 75% of the 1995 value). Note that this lower PMP would result in lower PMF (assuming all other PMF inputs remain unchanged) and indicate that the dam could safely handle more than 75% (and possibly 100%) of the new PMF, likely bringing the costs of dam safety improvement down significantly from the original $250 million estimate.

The Cherry Creek Dam is a good example where additional information obtained through a stochastic flood study could be applied to enhance dam safety critical decisions and justify cost and effort of undertaking the study. The full probability distribution (with uncertainty) of all flood characteristics would help in assessing the conservatism (i.e. AEP) of different PMF estimates as well as in making risk informed decisions on potential dam safety upgrades.

In addition, the availability of the full probability distribution of various flood characteristics allows us to estimate joint probabilities and identify potential failure modes that cannot be analyzed using strict “pass/fail” deterministic design criteria (e.g. dam failure due to a modest flood combined with a failure of one or more spillway gates).

As mentioned in the introductory section of this chapter, dams often fail during a non-extreme flood, due to a combination of two or more relatively usual unfavourable events, which individually are not safety critical. Therefore, the stochastic flood simulation approach for dam safety introduced in this chapter, despite being technically complex and carried out by only a small number of specialists, represents a valid and necessary alternative to standard-based deterministic methods, especially when risk estimates and associated dam safety decisions/operating policies are required over the full range of hydrologic loading conditions.

Finally, with intrinsic levels of uncertainty that will never be resolved, “satisfying yourself that you have results that can be relied on to make dam safety critical decisions” becomes a matter of acceptance of some residual level of risk. Applying the most rigorous scientific analyses to improve the understanding of these uncertainties is the best that any owner or regulator can do to satisfy themselves they have done as much as is practicable in arriving at their decisions.

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4. RESERVOIR INFLOW PREDICTION FOR PROACTIVE FLOOD RISK MANAGEMENT

4.1. FUNDAMENTALS AND BASIC PRINCIPLES OF HYDROLOGICAL AND HYDRO-METEOROLOGICAL INFLOW PREDICTION

Inflow prediction is the art of estimating the further development of reservoir inflow (and—additionally—preferably a measure of uncertainty/reliability) with the aim of fostering specific demands and informed decisions connected to reservoir operation at a wide range of temporal scales. The fundamental problem tied to the task of forecasting is, that an unknown future state has to be inferred from a mostly limited and erratic prior knowledge of the considered system. Regarding the aforesaid, forecasting strategies, methods, etc. have to be somewhat oriented toward the specific situation, problem, or management context.

Following this philosophy, the herein touched aspects should be discussed alongside the different temporal scales at which specific management problems are dealt with and management decisions are effective (Table 4.1).

Table 4.1 Temporal scales and their connection to typical reservoir management problems, associated with inflow estimation and flood risk management

Temporal scale	Long-term	Seasonal	Single-event
Management problem	Storage planning	Dam release management	Dam release/spillway management
	Design and optimization of rule curves	Withdrawal management	(Withdrawal management)*
	Climate change adaption	Water quality management	(Water quality management)*

**Set in brackets since measures are only effective to a certain extent on the respective temporal scale*

4.1.1. Forecasting/prediction methods

There is extensive literature reviewing the methods and their applicability for reservoir inflow forecasting, e.g., Easey et al. (2006) and WMO (2011), to name only two sources. When dealing with the matter, an individual assessment of the current literature is strongly recommended. Typically, in the literature, methods which are applicable for reservoir inflow forecasting are classified according to Table 4.2. Furthermore, the table lines out the suitability of these methods regarding the temporal scale, and therefore the set of reservoir management problems, given in Table 4.1.

Table 4.2 Suitability of different methods for inflow prediction and forecasting according to the temporal scale of interest

	Method/suitability		
Temporal scale	Statistical methods	Downscaling	Dynamic modeling
Long-term	+	+	—
Seasonal	+	+	+
Single-event	+	—	+

Statistical methods incorporate mathematical models that only address the input-output transfer-behavior of the considered system and explicitly do not regard the underlying physical processes. Typical representatives for this group of models are regression models, fuzzy-logic models and artificial neural network models. The clear advantages of statistical models are their usually straightforward and robust conceptualization, parameterization and operation. Typical shortcomings are the high demands regarding the amount and quality of required data and the limited spatial transferability alongside with partly limited temporal extrapolation behavior (considering event magnitudes which are not covered by underlying empirical data).

Dynamic modeling methods rely on an abstract, mathematically expressed conceptualization of the physical processes which are inherent to the considered system. This representation can either be directly oriented towards the occurring processes (usually by incorporating the governing physical conservation laws) or rely on a more abstract, yet representative portrayal of reality, e.g., via variable storage-tank models, which are very common in engineering hydrology (Ponce, 1994, to name only one). Dynamic modeling has the highest potential for an accurate representation of reality. On the other hand, dynamic models are virtually arbitrarily demanding in terms of conceptualization, parameterization and operation.

Downscaling methods hold an intermediate position in the way that they can rely on either statistical or dynamic modeling. The aim of downscaling is to project the output of long-term (e.g., climate models), seasonal, or short-termed circulation models ("weather models", "atmospheric models", or "numerical weather prediction [NWP] models") to spatial scales which are applicable for inflow prediction, e.g., for the underlying rainfall-runoff/water balance modeling. Circulation models (CMs) can be applied at global, regional or local scale; commonly, nested model chains are operated, where a global CM (GCM) yields the boundary condition for a regionally nested regional CM (RCM) and the RCM in turn drives a local CM (LCM) with typical horizontal resolutions of few to some kilometers.

It should be mentioned and underlined that the decision for or against a specific modeling approach should essentially be as simple as possible and as complex as necessary.

4.1.2. Decision making based on potentially uncertain forecasts

Uncertainty is inherent to the Earth system and to our knowledge of this system. The knowledge of uncertainty can help in fostering and informing decisions. In this light, uncertainty becomes useful and could be considered as a characteristic of reliability, something which is definitely desired in operational engineering tasks and also, e.g., for reservoir-related dimensioning purposes. Regarding the herein discussed problem of inflow forecasting and ignoring the fact at this point that there are different sources of uncertainty, it is of very importance to understand that the uncertainty of the inflow forecasting problem is steadily dependent on lead time and the spatial scale or scope (Figure 4.1); uncertainty usually will rise with increasing lead times and a decreasing spatial scale.

The aim of uncertainty analysis is to gather information on the chance of occurrence of a specific event (e.g., a specific flow rate or flow volume) in the form of a probability distribution, also called the **predictive uncertainty**. It is important to note that this probability distribution is conditional on the aforementioned errors and uncertainties, as well as their statistical interdependence and therefore represents the prior knowledge of the future for the point in time where the forecast is created.

Hydrological forecasts are affected by uncertainty, emerging from various sources (Grundmann, 2010; Klein et al., 2016). Basically, uncertainty is distinguished in **aleatoric** and **epistemic** uncertainty. Aleatoric uncertainty is the statistic uncertainty, emerging from the limited knowledge of the Earth system and its abstraction in the context of models. Epistemic or systematic uncertainty emerges from an insufficient knowledge of the considered system and its state and causes input parameter uncertainty, structural/model uncertainty, model parameter uncertainty (e.g., time steps, convergence criteria, etc.), and process parameter uncertainty (i.e., the physically-based or conceptual “hydrological” parameters).

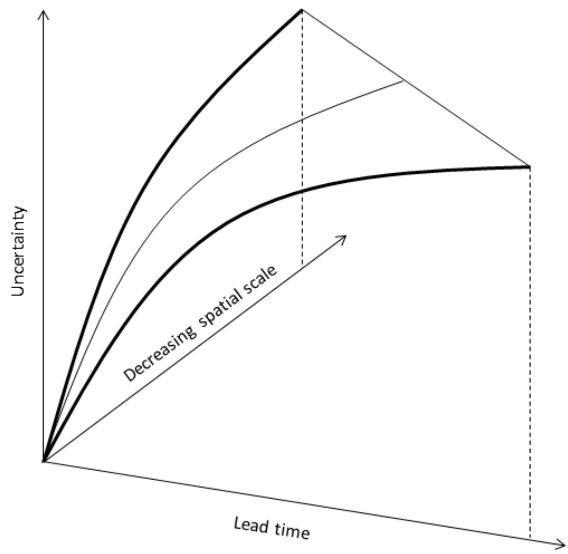

Figure 4.1 Conceptual illustration of the dependency of predictive uncertainty on increasing lead time and decreasing spatial scale

This said, it is clear that when decisions should be informed and when looking at the usually meso-scale catchment areas of multi-purpose reservoirs, a significant amount of predictive uncertainty will be present, should be assessed and, in turn, could be made available for informed decision making. However, uncertainty quantification is not straightforward when it is performed according to the state of the art in sciences and technology and can be demanding in terms of methodological and/or computational demand. With reference to the aforementioned principle of Occam's razor ("As simple as possible and as complex as necessary"), uncertainty estimation should therefore be only applied when these premises are on the table and clear to all involved decision makers. In contrast, a limited, methodologically insufficient uncertainty estimation should only be pursued with caution since it will likely lead to wrong or erratic decisions (Todini, 2016).

Most crucial for taking informed decision is the step of risk assessment. For instance, when there is information on target storage threshold exceedance for a specific lead time in terms of a probability[5], it has to be clear what the "risk tolerance" should be or, in other words, when action is taken (e.g., evacuate water to provide volume for retaining predicted flood events). It is indicated that risk assessment is placed on a preferably solid ground of information, for instance by simulating costs and benefits emerging from specific management decisions with

[5] E.g., resulting from an uncertainty analysis.

regard to multi-criteria operational requirements (e.g., flood protection and water supply). Last not least, it should be mentioned that emotion always plays a role in framing a decision (e.g., Kahneman & Tversky, 1979; Druckman & Mcdermott, 2008). That is why altered/optimized/improved management plans should always be developed and discussed with the operational personnel on the ground and potentially affected stakeholders.

4.2. PREDICTION-BASED FLOOD RISK MANAGEMENT ON DIFFERENT TEMPORAL SCALES

As already presented (Table 4.1), inflow forecasting strategies for different flood risk management purposes are oriented to a specific temporal scale (long-term, seasonal, short-term/single event). Typically, different management decisions are made on the basis of specific model-based analyses. For instance, for long-term dimensioning tasks a (statistical) time-series model may be appropriate, whereas for operational flood-control purposes, a real-time rainfall-runoff simulation approach, coupled to a weather forecast model may be preferred. Briefly said, there is no overarching approach capable of fostering the wide range of reservoir-related management and planning decisions (Table 4.2).

However, the recently emerging paradigm of **seamless prediction** aims at bridging the gaps between event-related forecasting to seasonal prognoses and even long-term considerations on the climate scale (e.g., Meissner et al., 2014). The advent of seamless prediction is directly connected to (a) the nesting of regional and local circulation models (RCMs/LCMs) within global circulation models (GCMs) and (b) the trend towards using (dynamic) GCMs as climate models, which was foremost driven by increasingly available computational power. An analog co-evolution is to be expected on the “hydrology side” where highly detailed models are more and more driven on regional up to continental spatial scales for analyses ranging from short-term water balance considerations up to long-term climate impact studies (e.g., see Samaniego et al., 2017).

4.2.1. Long-term scale

Long-term inflow prediction/estimation is important in two different contexts: (1) for the initial dimensioning of the storage of a planned reservoir and (2) for verifying, adapting and potentially improving management strategies for changing (i.e., non-stationary) boundary conditions, namely as a consequence of climate change.

4.2.1.1. Inflow forecasting/prediction strategies on the long-term scale

Long-term inflow prediction/estimation can be achieved by **statistical/stochastic modeling** on the one hand and **downscaling** from weather/climate model output on the other hand (see Table 4.2).

Historically, the state of the art in long-term inflow prediction was empirically based on observed (or estimated, e.g., via continuous rainfall-runoff modeling) inflow time series of limited length. The simplest (but still to a certain extent skillful!) strategy would be drawing a climatology out of the empirical observations and use it as a predictor for inflow estimation. To strengthen the statistical basis of the underlying data and to finally infer information on the reliability of results, **component-based time series models** then became the method of choice. Such models typically assume that a time series is composed by superimposed information of statistical moments (e.g., expected value, variance, skewness and kurtosis), periodicity and autocorrelation, trend (i.e., non-stationarity), and a stochastic (i.e., random) component ("noise" or residuals). Such an approach can be formalistically expressed as:

$$x_i = d_i + p_i + t_i + e_i$$

with x_i :… time series elements,
d_i :… deterministic component,
p_i :… periodicity,
t_i :… trend component, and
e_i :… stochastic/probabilistic component;
a multiplicative composition is also applicable.

The general approach of time series modeling is to estimate the components of the (additive or multiplicative) time series model by applying suitable methods to the empirical observation data (e.g., estimation of statistical moments, trend analyses, spectral analyses, like Fourier transformations, etc.) in form of a so-called decomposition[6]. This way, a (stochastic) time series model is parameterized and can then be used to reproduce the characteristics of the observed time series by running it sufficiently often. The set of output time series can then be delivered to the actual management/dimensioning/planning evaluations (e.g., a sequent-peak procedure for supply storage dimensioning; Potter, 1977 or more complex, so-called generalized reservoir-system operation models [GRSOMs]; Müller, 2014) which provides an empirical distribution of statistically equivalent results which in turn can deliver a reliability/probability information (e.g., supply security) via an appropriate frequency analysis.

[6] There is a plethora of decomposition techniques. Despite still being often used, the classical decomposition based on the mentioned additive or multiplicative time series concept has a number of flaws and several much better methods are available by now (Hyndman & Athanasopoulos, 2018).

Typical time series models which have been employed for long-term inflow predictions are linear auto-regressive types, e.g., like the much used Thomas-Fiering model (Fiering, 1971). In recent time, more sophisticated, potentially non-linear models, like Wavelet approaches, exponential smoothing or autoregressive conditional heteroskedasticity (ARCH) models emerged, to name only a few. An entry to this wide topic is provided by each good textbook on time series modeling in sciences (e.g., Hyndman & Athanasopoulos, 2018). It needs further to be mentioned that—as a consequence of their flexibility and ability to portray arbitrarily complex nonlinear functions—neural network models are also well-capable of portraying observed time series and being widely used for time series generation.

The other main path for long-term inflow estimation is made up by **downscaling approaches** employing dynamic modeling methods. The philosophy here is to use observed or projected (i.e., from climate models) rainfall, climate data, etc. and to perform retrospective/projective hydrologic (i.e., rainfall-runoff) modeling analysis (Beven, 2012). Since historic data may be rare, a quite new but potentially promising strategy is posed by so-called global reanalysis data. Such data is generated by running a GCM in retrospective mode (called hindcasting). Of course, reanalysis data may hold a vast amount of uncertainty which can be potentially assessed by incorporating probabilistic reanalysis products (like NOAA/CIRES, for instance) and applying ensemble techniques. Depending on the spatial resolution of reanalysis data, the further use of downscaling may be indicated (by employing nested RCMs and LCMs). Usually, climate model output not only covers a reanalysis part (e.g., 1950 to 2015), but also a projected time frame (e.g., 2015 to 2100), which of course could also be used as input for long-term hydrological modeling.

It should be mentioned that circulation model output will not necessarily match the local conditions (e.g., the climate or rainfall characteristics of a reservoir catchment) exactly. Therefore, it might be indicated to correct the CM and/or hydrologic model output to better portray local conditions, which is called **bias correction**. There is a vast number of methods for performing bias correction of CM output to be found in the literature, whereas an individual assessment is strongly recommended.

4.2.1.2. Excursus: Multi-criteria optimization

Long-term management problems typically address storage planning, design and optimization of rule curves (or guide curves), or questions of climate change adaption. Usually, multi-purpose reservoir management faces multiple, partly contradictory objectives, e.g., flood protection, power generation or drinking water withdrawal/supply. Hence, an integrative approach needs to anticipate that there is not a single optimal solution to a specific problem, but rather a whole set of **compromise solutions**, which are called the **Pareto-optimal** solutions.

A specificity of multi-purpose reservoir management is that the intended operational purposes usually are competing, e.g., flood retention (requires a preferably large cleared storage volume) vs. water supply security (preferably widely filled storage) vs. energy generation (preferably large pressure head/reservoir water level). The most common way of dealing with this issue in terms of optimizing reservoir management strategies is employing the concept of Pareto-optimality (Figure 4.2).

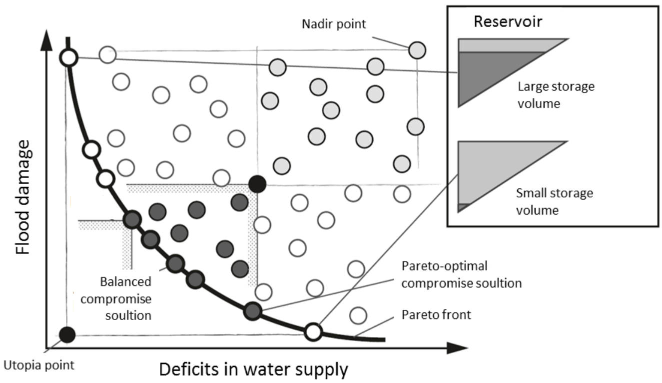

Figure 4.2 : Illustration of the Pareto principle.
Figure modified after Müller, 2014

The n points represent the outcome (in terms of specific objective functions) of *n* management scenarios regarding the competing purposes flood retention and water supply. So-called compromise (or Pareto-) solutions are located along the Pareto front, whereas the compromise solution located nearest to the Utopia point (lower left corner) usually is considered as being balanced with respect to the competing operational demands.

The concept of Pareto-optimality is closely tied to a **multi-criteria optimization** approach where all relevant optimization criteria (e.g., minimal flood damage alongside with maximum water supply security) are simultaneously considered. The methodological challenge to that problem is to apply an efficient and ample optimization strategy to get a sufficiently fine impression on the Pareto front without the need of processing all (i.e., an infinite number) possible management scenarios.

For engineering purposes, multi-criteria optimization is most often executed by means of simulation-based approaches, i.e., management premises are established, a generalized reservoir-system operation model is used to compute the impact of these specific premises on the interesting variables (e.g., storage volume, release rate, pressure head) and the results are then assessed using multiple criteria. To cope with potentially excessive computational demands, appropriate sampling and/or recombination techniques are essential in order to efficiently sample the (a priori unknown) solution domain (e.g., Vrugt et al., 2003; Krauße et al., 2012; Müller, 2014).

4.2.1.3. Considering uncertainty on the long-term scale

On the long-term, uncertainty can be considered as a **measure of reliability**. Reliability is a statistical term which is tied to considering a sufficiently large number of outcomes in order to evaluate their appropriateness towards a specific aim. However, our knowledge on the governing processes (e.g., inflow time series) is limited (aleatoric uncertainty; Section 4.1.2). This means that long-term considerations have to be executed not only once (i.e., deterministic) but often (i.e., probabilistic/stochastic). Again, this can be achieved by means of statistical/stochastic methods or by downscaling approaches (Table 4.2 and Section 4.2.1.1).

In the domain of statistical/stochastic methods, time series modeling (Section 4.2.1.1) is used to generate a sufficiently broad set of synthetic time series in order to appropriately sample the statistical properties of the underlying, observed empirical data. Finally, the set of synthetic series can be included in further steps, e.g., dimensioning considerations. For instance, driving a storage dimensioning model (e.g., like the Sequent Peak Algorithm, to name only a common and simple one) for n times (for n synthetic input time series) will lead to n results/capacities which then can be statistically evaluated, for instance, in terms of drawing exceedance probabilities/reliabilities for a given storage capacity.

It is important to check, if the pool of synthetic (i.e., "generated") time series resembles the original time series, which was a priori used for the parameterization of the time series model. This is exemplarily shown in Figure 4.3 for different moments/parameters of mean monthly inflow values (mean, standard deviation, skewness coefficient, and the coefficient of autocorrelation). Basically, moments of higher order (like the skewness) tend to show a higher variance when the synthetic series are compared against the original time series.

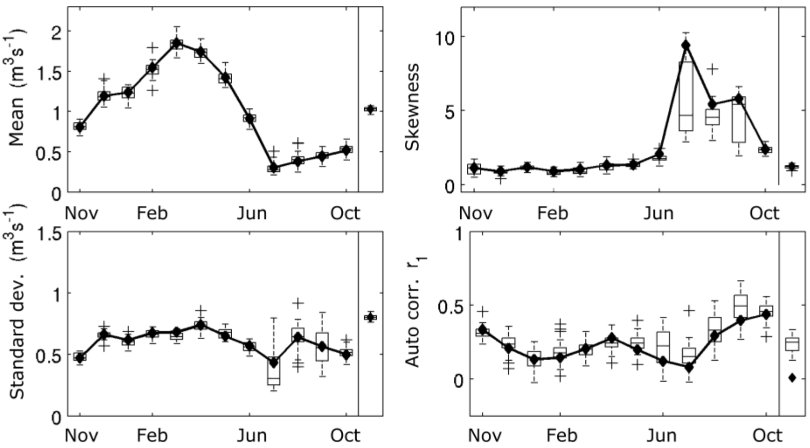

Figure 4.3 : Statistical Moments of monthly flow data - Modified after Müller (2014).

On Figure 4.3 the historical data are represented by the bold black line. The box plots shows the range of empirical data of the pool of generated time series. The right-hand section of each panel shows the annual mean value of the considered statistical moments (125 time series and time series length is 80 years).

Another aspect for evaluating the statistical robustness of the synthetic data pool is to determine the convergence behavior of the time series' statistical properties, e.g., represented by their statistical moments. As an example, Figure 4.4 shows the convergence of the standard deviation vs. the number of realizations (i.e., number of generated time series) for seven different input time series.

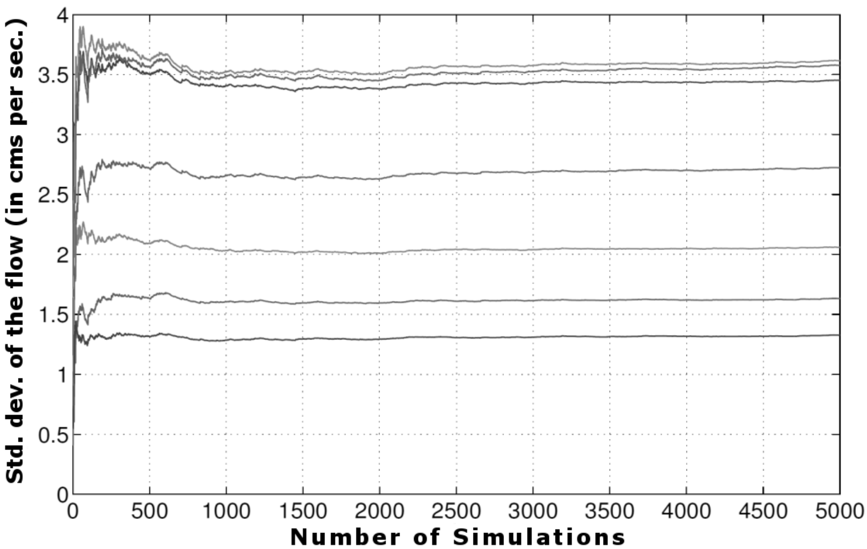

Figure 4.4 : Convergence of the standard deviation of synthetic time series (y-axis) depending on the number of generated series (given on the x-axis). Modified after Grundmann (2010).

Opportunity for uncertainty estimation is also offered via the methodological path of downscaling of circulation model output. For instance, there are probabilistic reanalysis datasets like NOAA/CIRES, which can be used to force hydrological modeling and to generate statistically interpretable inflow forecasts. On the projection side, different climate forcing scenarios are typically used to generate an ensemble of climate predictions. Furthermore, there are a number of ensemble climate projections available. Again, as already stated in Section 4.2.1.1, an appropriate bias correction of CM input (preprocessing) and/or hydrological model output (postprocessing) might be indicated, whereas this is beyond the scope of this publication and would require an individual review of the relevant literature.

4.2.2. *Seasonal scale*

"Seasonal scale" usually refers to a time scale ranging from weeks to months. Typically, management decisions are more influential on the seasonal than on the short-term side (Visser, 2017). For instance, the potential for a short-termed, operational mitigation of already observed or short-lead predicted flood inflow remains very limited, e.g., due to the limited hydraulic capabilities of the release devices and installations. Therefore, predicting the inflow regime on the seasonal scale is most crucial for undertaking informed reservoir management decisions, especially with regard to balancing multiple management purposes. However, seasonal inflow forecasts may not be able to deliver skillful predictions every time (Turner et al., 2017); despite more and better seasonal forecasting systems are emerging, it is still with significant effort to raise the skill above a certain baseline, given by flow climatology data (Section 4.2.2.1). A very profound review of the current state of the art in seasonal hydrological forecasting can be obtained from a special issue of HESS (edited by Wetterhall et al., 2016-2018); Easey et al. (2006) give much briefer review.

4.2.2.1. Inflow forecasting/prediction strategies

The most basic **statistical inflow prediction** technique is to rely on the **climatology** inherent to flow data, i.e., "historical" data". Flow data can be instantly available through gauging measurements or can be obtained by regionally transferring flow measurements from upstream or downstream locations or neighboring catchments. Additionally, flow data can be obtained by driving hydrological (rainfall-runoff) models by observed or reconstructed (i.e., reanalysis) rainfall and weather data.

Of course, for deriving a somewhat significant prediction of flows from empirical/historical data, the incorporated time series need to be sufficiently long. However, the statistical assessment of long time series offers a way to quantify uncertainty or exceedance/non-exceedance probabilities, respectively (Figure 4.5 and Section 4.2.2.2).

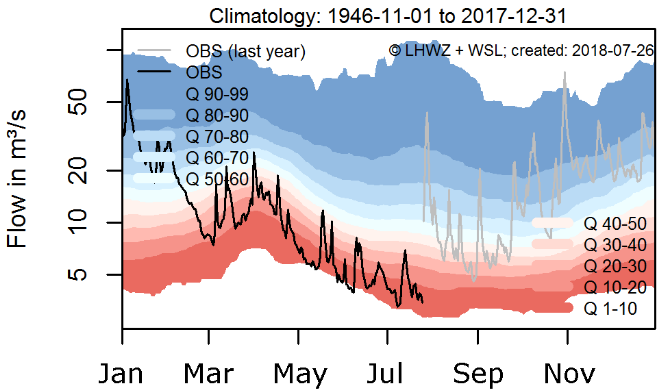

Figure 4.5 : Quantile-based flow climatology for river gauge Görlitz at Lausitzer Neiße River, Germany.[7]

Turning to more elaborate statistical methods, a broad field is made up by **regression methods** (typically multiple linear regression methods), where, e.g., antecedent conditions and specific climate indices (e.g., teleconnections) are used as predictors for streamflow (Ionita, 2017 or Charles et al., 2018, to name only two). In other words, those methods are based again on historical data and intend to "find statistically significant relationships between one or more predictors and the target variable of interest, e.g., river flow or precipitation" (Easey, 2006). However, these approaches always introduce the (unrealistic!) assumption of stationary.

It is of highest importance to account for errors and biases—which inevitably emerge by employing statistical methods—by appropriate post-processing approaches. Foremost, **bias correction** techniques are used to reduce statistical errors and to adjust model results to observed data/climatology. Despite the task of bias correction is almost indispensable when applying statistical prediction techniques, the frame of this chapter does not allow for a more in-depth elaboration on the topic. For further reading, Crochemore et al. (2016) deliver a profound entry to the topic.

Seasonal inflow predictions can further be obtained by employing **dynamic modeling techniques**. This might be the method of choice when meteorological forcing drive the streamflow predictability (Arnal, 2018), which is usually the case for smaller catchments (e.g., the headwater catchments of reservoirs). Seasonal circulation models (e.g., ECMW's System 4[8] or NOOA's CFSv2[9]) can deliver skillful forecasts of meteorological parameters with a lead time of several weeks

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[7] Climatology is empirically drawn from daily flow data from 1946 to 2017 and can deliver a probabilistic estimate on seasonal flow conditions.

[8] https://www.ecmwf.int/en/forecasts/documentation-and-support/evolution-ifs/cycles/seasonal-forecast-system-4

[9] http://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2_body.html

to some months. In turn, these meteorological forecasts can be used for driving a (already calibrated) hydrological model, delivering seasonal reservoir inflow predictions. As already mentioned alongside statistical prediction techniques, bias correction/calibration techniques usually need to be applied in order to improve forecasting skill.

Circulation models are available for different specific spatial and temporal scales; the aim of **downscaling** is to project the output seasonal circulation models to spatial scales which are applicable for the intended inflow prediction task (i.e., a subsequent rainfall-runoff modeling). This can either be done by "nesting" higher-resolved circulation models within coarser seasonal forecasting system or by using statistical techniques to infer the regional shaping of rainfall and all other relevant meteorological drivers from a more common (e.g., global) circulation model. In recent years, skillful seasonal meteorological forecasting systems did rapidly evolve. In this light, it seems legit to assume that quite highly (spatially and temporally) resolved seasonal weather forecasts data will be more and more instantly available in the near future.

4.2.2.2. Considering uncertainty on the seasonal scale

One of the oldest and maybe the most common method to inform reservoir release decisions on the seasonal scale incorporating uncertainty (at least to a certain extent) is a technique called **Ensemble Streamflow Prediction**, developed initially for California (ESP; Wood et al., 2016). According to Arnal (2018), ESP "relies on the correct knowledge of the initial hydrological conditions (i.e., of snowpack, soil moisture, streamflow and reservoir levels, etc.) and a large land surface memory, and contains no information on the future climate". The information "on the further climate" was obtained by EOF analyses (empirical orthogonal functions) which related indices like the Pacific sea surface temperature (SST) to future California climate, for example. Since EOF thrives from harmonic analysis, the methodology was capable of not only delivering one, but a whole set of future predictions (i.e., the ensemble; Figure 4.6). This, in turn, allowed for deriving failure probabilities for reservoir levels over a future period of up to six months.

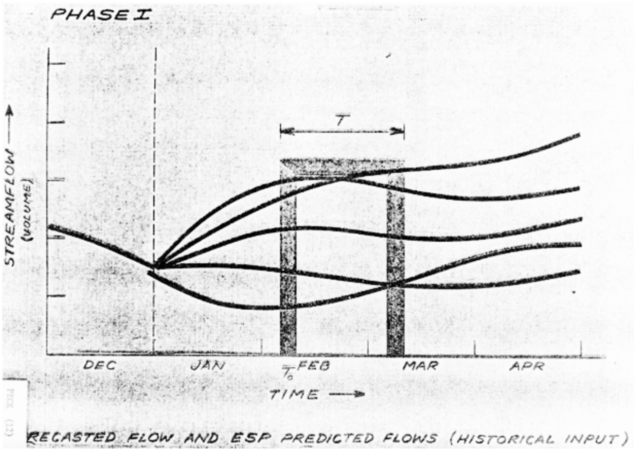


Figure 4.6 : An ESP illustrated by J. C. Schaake in 1978, from "Extended streamflow prediction techniques: description and applications during 1977", taken from Wood et al., 2016.

Nowadays, uncertainty information can be drawn from ensembles emerging from **seasonal ensemble forecasting systems**, like the already mentioned ECMWF System 4 or NOAA's CFSv2. These systems deliver ensembles by letting the circulation models run several times under slightly altered ("perturbed") initial conditions (and maybe other parameters, e.g., cloud physics parameters, etc.). Another way of obtaining ensembles is to combine the output of different models (so-called multi-model ensembles). However—as stated a couple of times throughout this chapter—in order to draw frequency/reliability information from an ensemble, it needs to be ensured that the statistical properties of an ensemble resemble reality. This is rather the exception than the rule and therefore, bias correction/calibration techniques should be applied.

Although the consideration of ensembles is not free of methodological burden, there are potential benefits for seasonal inflow prediction in terms of reliability, robustness, and statistical significance. Further reading on the matter can be obtained from Huang & Loucks (2000) or Georgakakos & Graham (2008), to name only two sources.

4.2.3. Short-termed, single-event scale

The practical importance of short-termed, single-event forecasts for reservoir management often remains limited. This is caused by a set of relevant, partly interdependent restrictions:

(1) Multi-purpose reservoirs are often located in smaller headwater catchments; hydrological reaction is swift and inflow forecasts must be based on hydro-meteorological forecast, in order to extend lead times to an applicable scale. However, it can be assumed that a skillful

meteorological forecast considering (heavy) rainfall events (those, that are primarily relevant for a proactive reservoir management), is only possible with a lead time of a couple of hours to some days, at most, depending on aspects like circulation patterns and the governing rainfall generation mechanisms. For instance, widespread frontal rainfall is predictable with a significantly better skill than convective rainfall, featuring a high spatio-temporal variability (Figure 4.7).

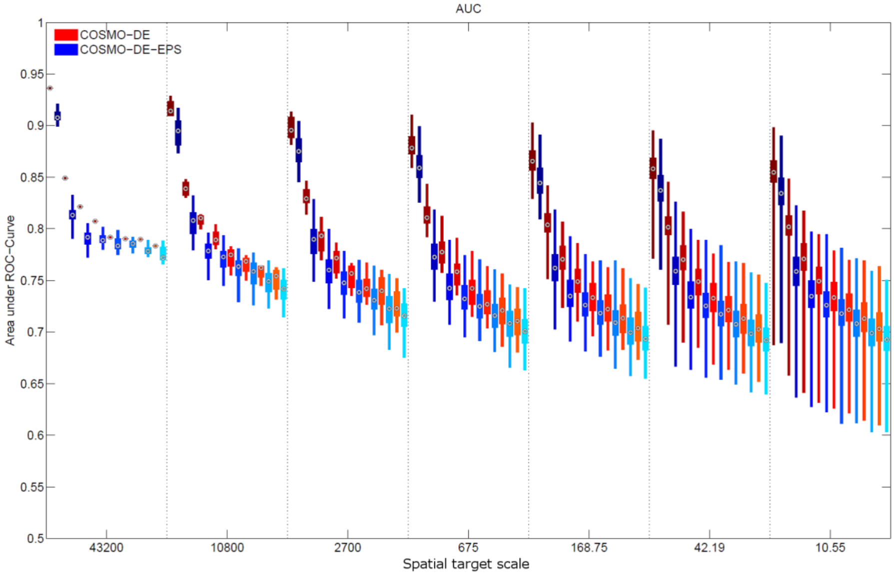


Figure 4.7 : AUC skill score for two different QPF products (COSMO-DE and COSMO-DE-EPS) depending on different lead times and different spatial scales.[10] Taken from Schütze et al. (2016).

(2) Especially on small spatio-temporal scales, inflow forecasts are encumbered with significant uncertainty. This uncertainty should be taken into account (e.g., with ensemble methods), which is partly methodically demanding and often hinders a pragmatic, operationally applicable uncertainty consideration. Furthermore, multi-purpose-reservoirs need to serve multiple, partly competing demands, e.g., flood protection vs. energy production. This leads to a pareto-optimal problem which means that an optimal solution can be established by a set of different solutions/considerations for each single operational purpose (Krauße, 2012 and Müller, 2014).

(3) Considering the potentially swift/flashy hydrological reaction and limited lead times (especially for small, fast-responding catchments), the technical ability

[10] The Y-axis shows the AUC. The X-axis indicates the range of spatial scales. AUC can be assumed to be “good” for values above 0.8. Each set of bars indicates one specific lead time [1, 3, 6, 9, 12, 15, 18, 21 hrs].

for an operational reaction is often limited, e.g., by the hydraulic capabilities of the release devices and installations.

(4) Rapid and short-term pre-event releases are not only constrained by technical limitations but are also dependent on the applicable legal framework. For instance, it is usually prohibited to increase pre-release rates to a damage-causing level (above rule release).

Figure 4.8 underlines the afore given points; the figure shows an example for Malter reservoir (East Germany; capacity: 8.78 million cubic meters, catchment area: ~105 km²) with actual and projected operational strategies during the extreme 2002 European Floods (return period > 100 years). It can be seen that even if there would have been a damage-causing (maximum damage-free downstream flow is ~15 m³/s) pre-release of 30 m³/s, starting from the point where the first official flood warning was disseminated, an effective peak reduction would not have been possible (yellow line). Furthermore, in order to reduce the outflow to a moderately damage-causing rate of 75 m³/s, the (already damage-causing!) pre-release would have needed to be initiated two days in advance, leading to a completely dry (!) reservoir by the onset of the flood event. Of course, this scenario is not applicable by any means, considering the remaining purposes of the reservoir and the tremendous uncertainties in the rainfall forecasts for a 100 km² catchment.

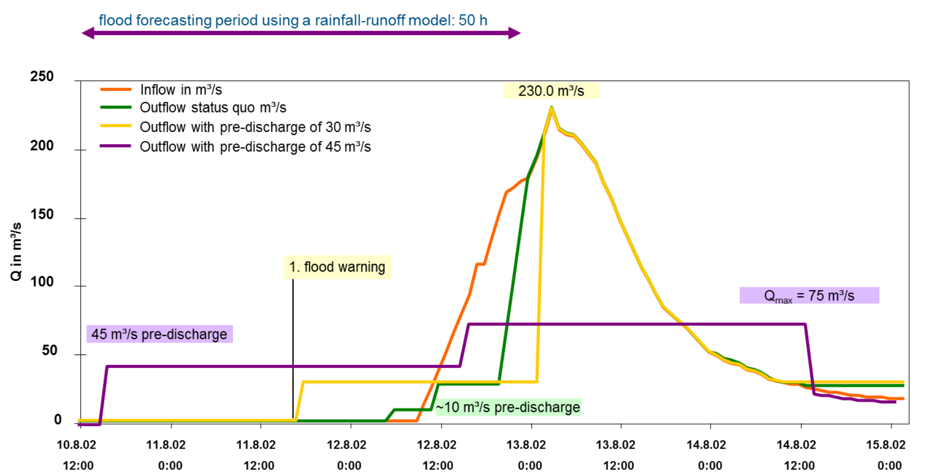


Figure 4.8 : Operation of Malter reservoir during the 2002 European Floods under different pre-release scenarios.

The description of the lines on Figure 4.8 is presented hereafter :

- Orange : Actual inflow;
- Green : Actual outflow;
- Yellow line : Projected (30 m³/s, starting from the initial flood warning;
- Purple line : Projected (45 m³/s, assuming a reliable, 48-hrs inflow forecast);

Data were provided by the State Dam Authority Saxony (LTV Sachsen) and the scenario analyses were from the Institute of Hydrology, Dresden University of Technology.

Notwithstanding the fact that the impact of short-term management decisions on reservoir operation is limited, it is still recommended, especially for smaller catchments, to assess the forecast benefit for a specific reservoir, operational strategy, etc. in order to determine the limits and also the potential benefits drawn from an inflow forecast. Therefore, the following two sections shed a light on short-term forecasting strategies and an easy method to determine the forecast benefit as a function of lead time, which can deliver an estimate on the minimum required lead times for an efficient release management.

4.2.3.1. Prediction strategies and aspects of operational short-term inflow forecasting

An applicable inflow forecasting strategy is dependent on different aspects. Of highest importance is the spatial scale/catchment area of the considered reservoir location. For larger catchments (say beyond 10,000 km²) or reservoirs on large rivers, the inflow can be forecasted by means of statistical modeling (regression models, neural networks, fuzzy models) or hydrologic/hydraulic process oriented models. Where there is upstream gauging data and the mean translation time from the upstream gauging locations to the reservoir site is sufficient for management purposes, a broad range of methods may be applied and will deliver quite reliable results.

If catchment size decreases to an intermediate scale (area of some thousands km²) and/or lead time should be extended, there is a need to include rainfall observations/estimates. First, this requires the employment of rainfall-runoff models; second, spatio-temporal rainfall estimation and rainfall forecasts will introduce additional uncertainty.

For small headwater catchments (area smaller 1,000 km²), rainfall forecasts are needed to at least ensure somewhat reasonable lead times. This, of course, introduces the highest amount of uncertainty and also requires spatio-temporal highly resolved rainfall-runoff modeling.

There are many other important aspects that need to be assessed when developing an operational short-term inflow forecasting system, e.g., data situation, operational robustness, implementation and operation costs, to name only a few. For further details, the WMO Manual on Flood Forecasting and Warning holds extensive information on the topic (WMO, 2011).

4.2.3.2. Excursus: Assessing the benefit of a forecast depending on lead time

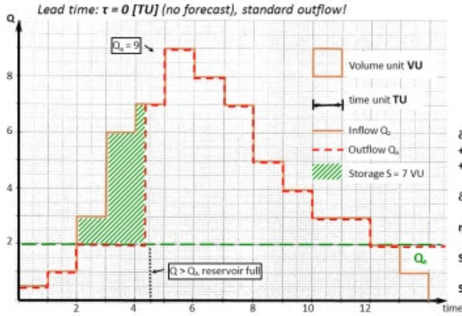
A meaningful extension of a forecast's lead time is at least costly or at worst impossible, when it comes to small catchments and/or larger lead times (i.e., beyond some days). Therefore, it is important to determine the relation of forecast benefit (e.g., in terms of peak outflow reduction[11]) and the lead time. A very basic consideration towards estimating this relation is described in the following (Figure 4.9):

The flood control volume should be assumed to be seven (7) volume units (VU). Furthermore, an inflow design hydrograph should be available (e.g., from hydrograph analyses or regionalization studies). For a lead time of zero (upper left panel in Figure 4.9), there would be no prior information/estimate for fostering a specific release control; therefore, release is just adjusted to the rule release rate (green horizontal line; assumed to be 2 VU/TU). This holds up until the flood control volume is exhausted (which is the case after 4+1/3 TU); release will then directly follow the inflow.

With extended lead time, there is a better prior knowledge on the expected inflow hydrograph (in terms of a "look-ahead"); therefore, controlled outflow would be modified (dashed line), leading to a better peak flow reduction. Expressing the peak flow reduction in mathematical terms can be done, e.g., by calculating the root-mean-square error (RMSE) between the status-quo outflow (for a lead time of zero) and the outflow for a specific, nonzero lead time. The inverse RMSE can then be interpreted as benefit, which is displayed in Figure 4.10 for the discussed example.

[11] Comparable methodology could be applied for other beneficial (and potentially competing!) reservoir functions, e.g., water supply.

Lead time: τ = 0 [TU] (no forecast), standard outflow!



$\delta(0) = 3/5 * 5^2 + 7^2 + 6^2 + 5^2 + 3^2 + 2^2 + 2*1^2$

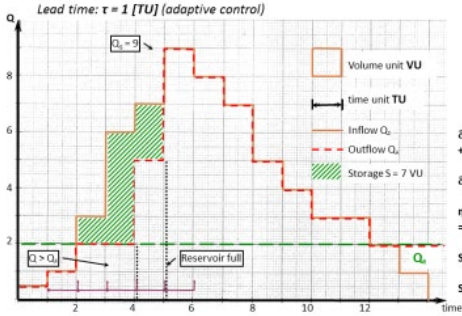
$\delta(0) = 140$

$\eta(0) = \delta(0) - \delta(0) = 0$

$S = 1 + 4 + 2/5 * 5$

$S = 7$ VU

Lead time: τ = 1 [TU] (adaptive control)



$\delta(1) = 3^2 + 7^2 + 6^2 + 5^2 + 3^2 + 2^2 + 2*1^2$

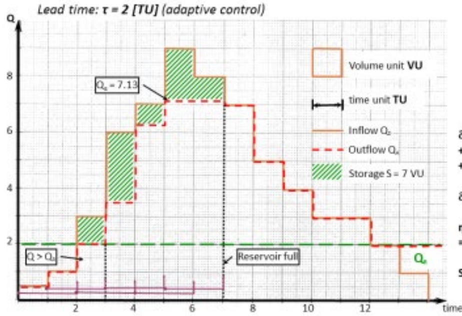
$\delta(1) = 134$

$\eta(1) = \delta(0) - \delta(1) = 140 - 134 = 6$

$S = 1 + 4 + 2$

$S = 7$ VU

Lead time: τ = 2 [TU] (adaptive control)



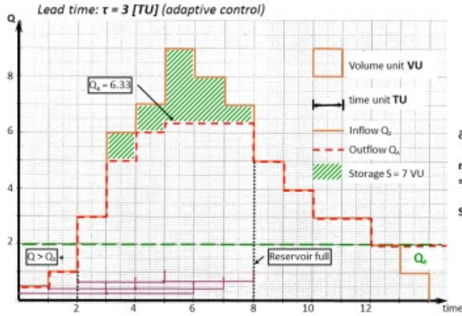
$\delta(2) = 1.5^2 + 4.25^2 + 5.125^2 *2 + 5^2 + 3^2 + 2 * 1^2$

$\delta(2) = 112.8$

$\eta(2) = \delta(0) - \delta(2) = 140 - 112.8 = 27.2$

$S = 7$ VU

Lead time: τ = 3 [TU] (adaptive control)



$\delta(3) = 97.3$

$\eta(3) = \delta(0) - \delta(3) = 140 - 97.3 = 42.7$

$S = 7$ VU

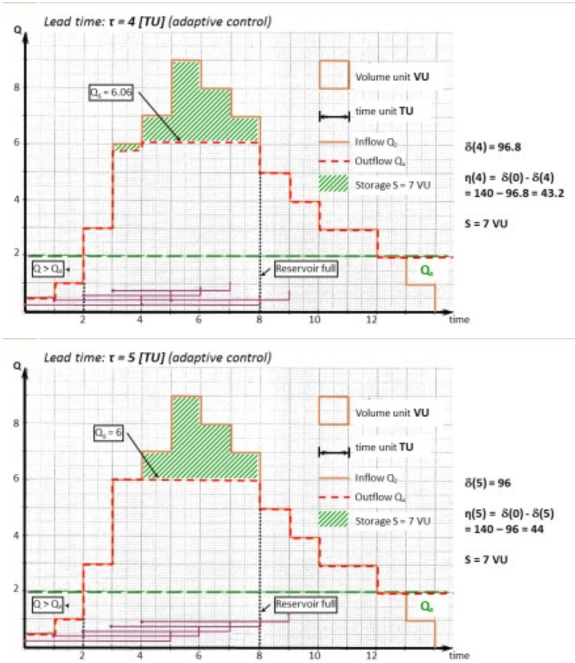


Figure 4.9 : Simple assessment of the forecast benefit (expressed as peak reduction) using a release strategy based on available look-ahead time (lead time).

It is assumed that the release can be freely regulated without hydraulic restrictions and with no time lag. Release is established using the specific available look-ahead data and regarding a maximum peak reduction within the range of the lead time.

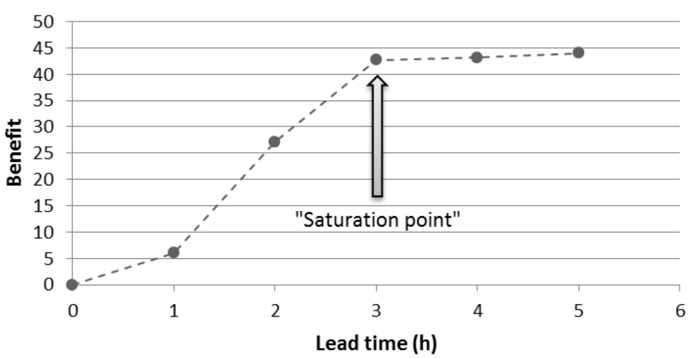


Figure 4.10 : Benefit (peak flow reduction) as a function of lead time (data according to Figure 4.9).

Figure 4.10 shows that the benefit is saturated beyond a specific lead time. By means of such a simple approach, it is at least possible to get a valuable estimate on the minimum required lead time for achieving a noticeable peak reduction. In turn, this is quite important since the implementation and operational costs, as well as the data demand of a forecasting system are directly depending on desired lead times.

4.2.3.3. Considering uncertainty on the short-term scale

For short-termed inflow forecasts for smaller headwater catchments, usually quantitative precipitation estimates (QPEs) and—additionally—quantitative precipitation forecasts (QPFs) need to be taken into account. QPFs introduce the vast amount of uncertainty in this case (input parameter uncertainty) and should therefore be the first in the focus when it comes to uncertainty analysis.

In hydrological forecasting, the aim should be to reduce the total uncertainty, e.g., by means of data assimilation, state updating and bias correction methods (WMO, 2011). On the other hand, which is even more important, dealing with uncertainty can produce an uncertainty quantification, which, in turn, can deliver an estimate on prediction errors or the reliability of forecasted values, for instance.

Typically, **ensemble methods** are employed for uncertainty estimation on shorter time scales. This means, that the aforementioned epistemic uncertainty ranges are sampled alongside a known or estimated prior distribution of the considered parameters. In the case of input parameter uncertainty, this is—for instance—typically done by using a set (or ensemble) of possible future realizations of the further rainfall development. This strategy delivers not only one (deterministic) output, but a set of outputs (the so-called raw ensemble).

The emerging set of outputs is **not** identical with the predictive uncertainty. Taking the raw ensemble as the basis for probabilistic estimations (e.g., via empirical quantile analyses) is methodically wrong, since the statistical interdependence of the (conditional!) uncertainty sources is ignored this way (Todini, 2016; Hernández-López & Francés, 2017 and see Figure 4.11).

For the sake of brevity, the concerning methods for joint (mostly Bayesian) uncertainty processing and predictive uncertainty estimation (like GLUE, BaRE, and BATEA, to name only a few) cannot be discussed in-depth within this frame. Rather the relevant literature in this field is recommended (Beven, 1993; Kuczera and Parent, 1998; Bates et al., 2001; Kavetski et al., 2002; Kuczera et al., 2006) whereas Grundmann (2010) and Klein et al. (2016) provide an easy access to this quite sophisticated topic.

However, it should be stated that a state-of-the-art uncertainty assessment requires properly conditioned probability densities (e.g., statistically representative and reliable ensemble forecasts, process and model parameters, and so forth; Todini, 2016), which is a very challenging objective in practice. Not least, potentially extraordinary high computational costs may and most likely will hinder the implementation of (especially Monte-Carlo based) methods in real-time sensitive contexts.

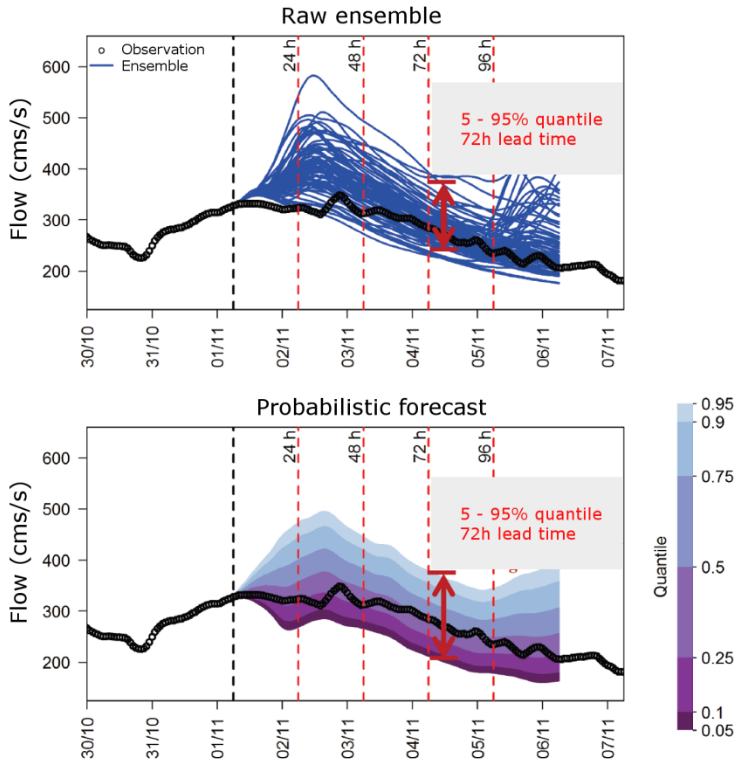


Figure 4.11 : Comparison of a raw ensemble (upper panel) and a processed ensemble as "true" estimate of the predictive uncertainty (below). From Klein et al. (2016).

A better coverage of the observed data by the probabilistic (lower panel) forecast (observations are always "within" the forecast ensemble) as well as the better sharpness/lower spread of the probabilistic product vs the raw ensemble can be noted on the figure. Further note that 10% of the estimated possible realizations of river flow lie outside the depicted 5-95% range.

4.3. DISCUSSION AND RECOMMENDATIONS

Long-term inflow prediction is important mainly for the sake of dimensioning. Despite statistical models introduce some major shortcomings (assuming stationarity, co-linearity or dependence of predictors; Wedgbrow et al., 2005), such approaches are still superior for long-termed predictions and are much easier to apply than dynamic modeling techniques (at least, when not using instantly available dynamic modeling output). Long-term inflow prediction is usually carried out by statistical/stochastic modeling or downscaling from weather/climate model output.

For **seasonal forecasting** purposes, dynamic circulation models nowadays hold a high degree of sophistication, are usually physically-based and should therefore be able to generally outperform statistical approaches. In practice, this is only the case for lead times of up to one or two months (Arnal, 2018). The limited knowledge of initial conditions (mainly due to lacking data) and the generally chaotic behavior of the Earth system jeopardize an exact prediction of the dynamic evolution of the atmosphere for lead times of more than two or three months. However, compared to the situation before 10 years (e.g., Easey et al., 2006), the skill of dynamic modeling approaches did improve a lot. The main reasons for that are better and spatio-temporally higher-resolved models together with improved computational resources on the one hand, as well as better data availability (mainly from satellite-based remote sensing) and strongly improved data assimilation techniques (e.g., 4D-VAR[12]) for inferring the initial condition of the Earth system, on the other hand.

Short-termed inflow forecasts extend to a couple of days. For reservoirs in smaller headwater catchments, such lead times would be sufficient for undertaking appropriate flood-control decisions. However, uncertainty of rainfall forecasts and the reliability of subsequent rainfall-runoff prediction is important for an informed decision-making. Unfortunately, the predictive skill of quantitative precipitation forecasts is limited with regard to small headwater catchments, especially for extended lead times in the medium range (up to two weeks). That is why the incorporation of uncertainty and proper predictive uncertainty estimation is important. For larger catchments, short-termed predictions can be carried out with essentially higher skill, even by using quite simple statistical approaches, given, that data which firmly correlate to the river flow (e.g., upstream flow data) are available.

Regardless the considered temporal scale and the specific prediction task, the consideration of **predictive uncertainty** is strongly recommended to better inform management decisions (e.g., Delaney, 2018). Especially for smaller headwater catchments, predictive uncertainty will strongly influence the reliability of model results and therefore can potentially jeopardize deterministic model results. However, a proper uncertainty estimation may be cumbersome in terms of methodology and technical demands and therefore should be thoroughly addressed in the conceptualization of inflow prediction projects and tasks.

4.4. CASE STUDIES

The following three case studies are presented in Appendix A :

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[12] https://www.ecmwf.int/en/about/media-centre/news/2017/20-years-4d-var-better-forecasts-through-better-use-observations

1. Long-term scale: Multi-objective optimization of multi-purpose reservoir systems under high reliability constraints - Germany
2. Seasonal scale: Seasonal (mid-range) forecasts for reservoir operation adaptation to mitigate shifting precipitation patterns - Germany
3. Short-term scale: Use of reservoir storage for flood operation in the Kumano River basin - Japan

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APPENDIX A
RESERVOIR INFLOW PREDICTION FOR PROACTIVE FLOOD RISK MANAGEMENT

CASE STUDIES

A1 - LONG-TERM SCALE

MULTI-OBJECTIVE OPTIMIZATION OF MULTI-PURPOSE RESERVOIR SYSTEMS UNDER HIGH RELIABILITY CONSTRAINTS - GERMANY

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1) Introduction

Most reservoirs in non-arid regions are managed with the aim to comply with municipal water supply security policies that require an occurrence-based reliability (Hashimoto et al. 1982) of 99.0 % or more. Simulation models allow for a rather complicated rule set and therefore are typically used to validate if the operation of a reservoir (given by a set of operational rules) can provide such high reliabilities. Simulation-based optimization methods are capable to solve problems that involve reliability (Koutsoyiannis and Economou, 2003) and can be used to find new operational rules or to optimize existing rules.

For this case study, a method by Müller and Schütze (2017) is used to derive best operational rules for the time period between 2021 to 2050 for climatic conditions, as given by the WETTREG-2010 projections (Kreienkamp et al., 2010) under the IPCC storylines (A1B, B1 and A2) for a reservoir system in Eastern Germany under high reliability constraints.

Multi-objective optimization is used in order to compare possible trade-offs between conflicting goals under changed climatic conditions, compared to the current status quo. Furthermore, optimally adapted operational rules are necessary for an unbiased assessment of reservoir performance under changed conditions (Eum and Simonovic, 2010).

2) Methodology

Estimation of future inflow conditions

To estimate inflows into the reservoir system under the WETTREG-2010 climate projections, water-balance simulations were carried out with the WASIM-ETH hydrologic model. Total inflows to the system are projected to decrease in average from 2.1 m^3/s (period 1921 to 2007) to 1.5 m^3/s in the scenario A1B, 1.8 m^3/s for scenario B1, and 1.6 m^3/s in the scenario A2, equaling a reduction of inflow volumes of up to 25 %. Of course, other statistical properties of the inflow are subject to change under projected change scenarios. More details can be found in Müller (2014).

Time series modeling/generation

The projected (deterministic!) inflow time series from the hydrologic model are then used as a basis to generate sufficiently long/many time series to further address reliability estimation purposes. A nonparametric, K-nearest-neighbor (KNN) neural network approach (Ashrafzadeh and Rizi, 2009) has been used for the stochastic simulation of lag-1 auto-correlated streamflows. The main advantage of the employed model, compared to other state-of-the-art KNN time series models, is the generation of inflow value magnitudes, which were not observed in the historical record. To prevent an underestimation of drought periods, the model was extended with a symmetric moving-average filter, similar to a method introduced by Langousis and Koutsoyiannis (2006). For further details concerning the time series model, see Müller and Schütze (2017) and Müller (2014). Statistics of the generated time series pool are shown in Figure A1.1. The length of the generated time series is 10,000 a.

Reduction of complexity: Shortening of time series by applying recombination techniques

Koutsoyiannis and Economou (2003) show that under simplified assumptions, a simulation period of several thousand years may be required in order to properly assess reservoir operations under high-reliability constraints (e.g., for 99 %). Running a simulation with such long time series is no huge demand with the computational power available with personal computers today. However, in simulation-based, multi-objective optimization frameworks, simulation models may need to be run for several thousand times. Here the computational demand proves to be an unacceptable burden. Müller and Schütze (2017) therefore proposed a method to reduce the length of time series significantly while preserving crucial statistical and stochastic features which are needed to accurately describe the inflow regime of a reservoir system.

The methodological steps comprise (a) the multivariate generation of long time series with KNN neuronal networks (previous section). Then, (b) drought periods in the time series are identified using the sequent-peak algorithm. In a final Monte-Carlo sampling step (c) a subset of drought periods is selected, such that the original distribution of deficit volumes is preserved. For details, see Müller and Schütze (2017). Properties of the resampled time series pool can be seen from Figure A1.1. Resampling of the time series led to a length of 800 to 1,000 years per series.

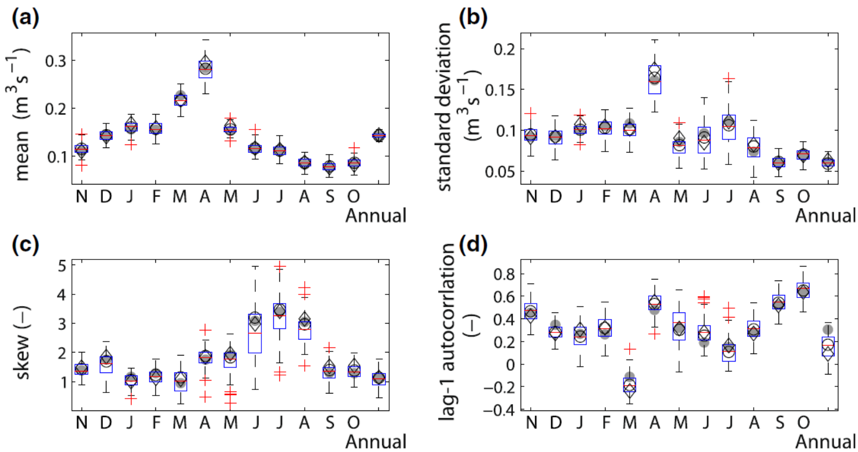

Figure A1.1 : Comparison of monthly and annual statistical properties of exemplary inflow data (inflow to Lehnmühle Reservoir) for 120 simulations from the KNN model (circles), historical flows (solid gray circles) and "shortened" (i.e., resampled) time series (diamond). Taken from Müller and Schütze (2017).

Generalized reservoir-system operation model (GRSOM) and multi-objective optimization

For the simulation of the water resources system, the widely used GRSOM OASIS (Hydrologics, 1991) is applied. OASIS uses a fast-mixed integer linear programming algorithm to distribute water per time step in an optimal manner. The built-in OCL programming language makes OASIS flexible and easy adoptable. The Multi-Objective Covariance Matrix Adaptation Evolution Strategy (MO-CMA-ES; Igel et al., 2007) was used for solving the multi-criteria/objective optimization problem (Section A1.4).

Level diagrams as a tool for the visual assessment of Pareto-optimal results

Blasco et al. (2008) introduced so-called level diagrams for visualizing high-dimensional Pareto fronts. The basic idea is to calculate the distance between each solution within a Pareto set, given in the fitness function space, and the Utopia point (the best, but non-existing, solution one could construct of each best value of each fitness function). For visualization, each fitness function has its own representation in the level diagram. Each solution is plotted with its fitness function value on the abscissa, and the respective value of the calculated distance to the Utopia point on the ordinate. A specific solution has the same position on the ordinate in each representation ("they are leveled"). This synchronization by means of the calculated norm on the ordinate holds the key to easily visualize high-dimensional data sets. As an example, in Figure A1.3, solution (2) is depicted for each sub plot with the same ordinate value.

3) The reservoir system

The reservoir system for the case study is located in the Eastern Ore Mountains in Saxony, Germany, to the southwest of the city of Dresden and comprises three reservoirs, namely Lehnmühle (LM), Klingenberg (KL) and Rauschenbach (RB), see Figure A1.2(a). The operational storage capacities of the reservoirs are 16.32 hm³ for KL, 19.42 hm³ for LM and 15.20 hm³ for RB.

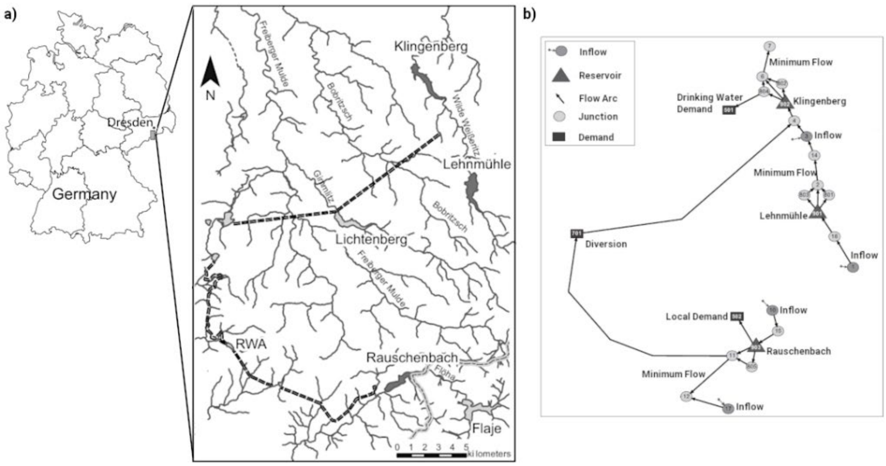

Figure A1.2: (a) Map of the reservoir system in the federal state Saxony in Germany and (b) illustration of the reservoir system in the simulation model OASIS.

The reservoir system has multiple purposes. Domestic, industrial and municipal water for the cities of Dresden and Freital is supplied by the reservoir KL. Ecological minimum flows need to be ensured; see Figure A1.2(b). Additionally, all reservoirs serve for flood protection, which is considered implicitly in this study, as the flood storages of the reservoirs need to be kept free in normal operation.

Domestic, industrial and municipal water is supplied according to the supply levels 1 to 3. These levels are governed by two monthly rule curves, $Z^{KL,1}$ and $Z^{KL,2}$, which divide the combined storage volumes of reservoirs KL and LM into three sections. With falling storage in both reservoirs, the supply rate is reduced according to Table A1.1(a). With decreasing supply, the associated reliability increases. To ensure a good water quality of the supply during a drought, reservoir LM is drawn down first to a specific threshold level and only after that threshold is reached, reservoir KL is drawn down subsequently.

Reservoir RB is supporting reservoir KL by providing water by means of a trans-catchment diversion system (“RWA” in Figure A1.2(a)). As applies for the supply of water by reservoir KL, the diversion is also governed by two monthly rule curves, $Z^{div,1}$ and $Z^{div,2}$, which divides the combined storage of the reservoirs KL and LM into three sections with individual diversion rates, see Table A1.1(b).

Table A1.1: (a) Supply Rates and required reliabilities for the three supply levels and (b) the diversion rates from reservoir RB for the three diversion levels.

(a)

Level	Rate (m^3/s)	Reliability (%)
Supply level 3	1.000	99.00 %
Supply level 2	0.925	99.50 %
Supply level 1	0.850	99.95 %

(b)

Level	Rate (hm^3/month)
Diversion level 3	0.0
Diversion level 2	0.4
Diversion level 1	0.6

4) Formulation of the multi-criteria optimization problem

Multiple operational purposes are often in conflict. Three fitness functions (FF) are considered in order to address the most important operational purposes in the frame of a multi-criteria optimization:

- FF1 maximizes the intended reliabilities (R) which are associated with the three supply levels (SL) and can be formally written as *max(FF1) = max(R(SL1) + R(SL2) + R(SL3))*
- FF2 maximizes the probability that the reservoir is filled up to target storage (i.e., "full") at the end of April in order to provide a good water quality during summer
- FF3 minimizes the total amount of water provided by reservoir RB in order to minimize pumping costs for water diversion

To obtain optimal operational rules, the four rule curves ($Z^{KL,1}$, $Z^{KL,2}$, $Z^{div,1}$, $Z^{div,2}$) are subject to optimization. Since storage values for the rule curves are needed for every month, the resulting optimization problem considers 48 decision parameters (4 by 12).

5) Results

Multi-objective optimizations were carried out for recent conditions (1921-2007) and three projected climate-change scenarios. In Figure A1.3, all Pareto fronts from all multi-objective optimization runs are plotted in a single level diagram and are ranked (three fitness functions FF1-3) against each other. Additionally, the achieved reliabilities R(SL1-3)) for the three supply levels are given. The representation of a single Pareto front of one optimization is surrounded by a hull, for better visibility. This is a novel interpretation of the original take on level diagrams by Blasco et al. (2008).

Regarding Figure A1.3, the "higher" (i.e., in positive ordinate direction) a single Pareto-front (within a hull) is, the less competitive the reservoir system is compared against "lower" (i.e., in negative ordinate direction) Pareto fronts from other scenarios (another hull). However, every solution of a single Pareto front (within one hull) is still an *optimal* management option for that scenario and the associated constraints!

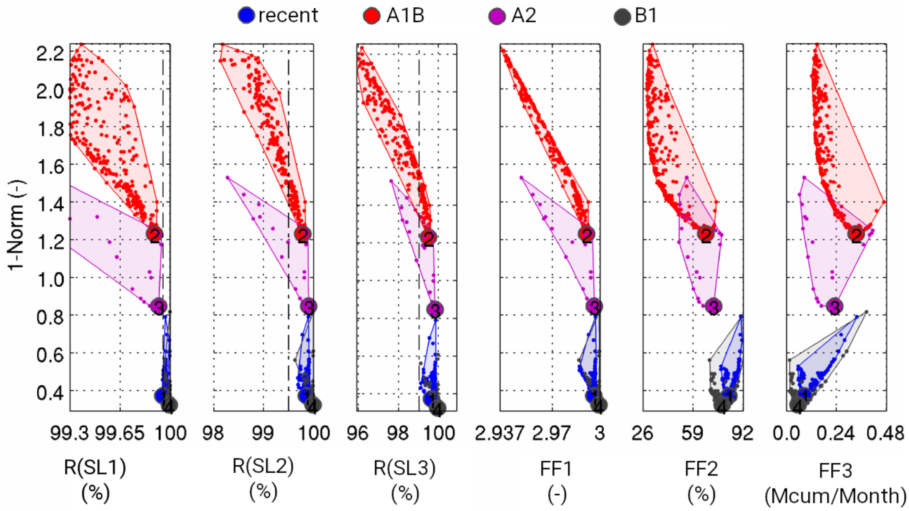

Figure A1.3: Modified Level-diagram showing the Pareto fronts for all optimization epochs: recent conditions (blue); 2021-2050 conditions A1B (red), A2 (pink) and B1 (gray).

The numbered solutions for a single Pareto front are the most balanced compromises between all contradictory purposes/management goals. Because of decreasing inflows when comparing the status quo with A2 to A1B conditions, the performance of the reservoir system decreases in general, the numbered solutions are situated “higher” on the ordinate. With increasing FF3 values from recent conditions to A1B, more water has to be diverted to reservoir KL to mitigate the decreasing mean inflows. Nevertheless, the chance of a filled reservoir KL in April decreases, as documented by simultaneously smaller FF2 values. Apart from that, scenario B1 is a special case. Despite slightly lower mean inflows to the reservoir system, less severe drought conditions are projected. Therefore, the overall performance of B1 is actually slightly better than under recent conditions. The most balanced solution of B1 has even a lower ordinate value than that of the recent scenario.

Table A1.2 provides additional information for a decision maker by listing the most extreme and balanced compromise solutions. Looking at the solutions with the maximum FF1 values, max(FF1), the required reliabilities can only be achieved in recent conditions and for B1. Under A1B and A2 conditions, the reliability for supply level 1 falls short of being met for A1B and A2. Additionally, higher diversion rates (FF3) are needed and the water quality may decrease because of smaller FF2 values.

Table A1.2: Summary of reliability assessment results for the three supply levels R(SL1) to R(SL3) and the fitness functions FF1 to FF3 for selected solutions for the scenarios (A1B, B1, B2) in 2021-2050 and under recent conditions (status quo). Reliabilities, which do not meet target reliabilities according to Table A1.2(a) are marked in red color.

Scenario	Solution	R(SL1) (%) Target: 99.950	R(LS2) (%) Target: 99.50	R(LS3) (%) Target: 99.00	FF1 (-)	FF2 (%)	FF3 (hm^3/ month)
Recent	max(FF1)	99.972	99.93	99.88	2.998	81.56	0.093
	max(FF2)	99.995	99.89	99.71	2.996	91.35	0.280
	min(FF3)	99.957	99.73	99.14	2.988	77.44	0.056
A1B	max(FF1) = max(FF2)	99.909	99.83	99.53	2.993	74.38	0.468
	min(FF3)	99.328	98.71	96.63	2.947	29.01	0.121
B1	max(FF1) = max(FF2)	99.998	99.99	99.97	3.000	92.91	0.290
	min(FF3)	99.964	99.63	99.09	2.987	69.93	0.015
A2	max(FF1)	99.921	99.90	99.82	2.996	72.55	0.232
	max(FF2)	99.937	99.88	99.27	2.991	77.80	0.400
	min(FF3)	96.252	93.71	87.01	2.771	39.00	0.001

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A2 - SEASONAL SCALE:

SEASONAL (MID-RANGE) FORECASTS FOR RESERVOIR OPERATION ADAPTATION TO MITIGATE SHIFTING PRECIPITATION PATTERNS – GERMANY

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1) Introduction

In recent years, changes in the precipitation patterns have been observed in Germany. Rainfall in February to April shifted more into the summer. Although total annual rainfall remained at nearly the same level, the resulting discharge decreased due to higher evaporation losses in the summer months. As a consequence, reservoir operators experience difficulties in reaching full supply levels in spring, which jeopardizes existing and competing demands and requirements over the course of the remaining year. This also impacts local communities and water suppliers. In addition, flood storage needs to be operated in a dynamic way, as the actual precipitation pattern might differ from the patterns used for designing flood storage volumes.

Thus, a preferably early recognition of droughts (or wet conditions) in order to plan and implement operational counter-measures is the objective of seasonal forecasting and its application for adaptive reservoir operation. The presented approach uses hydro-meteorological indices based on observations from ground stations and seasonal forecasts of precipitation for up to 9 months in order to identify the need for operational counter-actions at a preferably early stage. Seasonal circulation forecasts of NOAA are used.

The approach is being tested for five reservoir systems with a total of ten multipurpose reservoirs in Germany. The first investigations started in 2013 together with the Water Board Eifel-Rur (North Rhine-Westphalia). The methodology is not only interesting for reservoir operators but also e.g. for mining companies which run complex wastewater-discharge schemes. For instance, the methodology is currently in the first stage of implementation in Hesse in the context of mining water management.

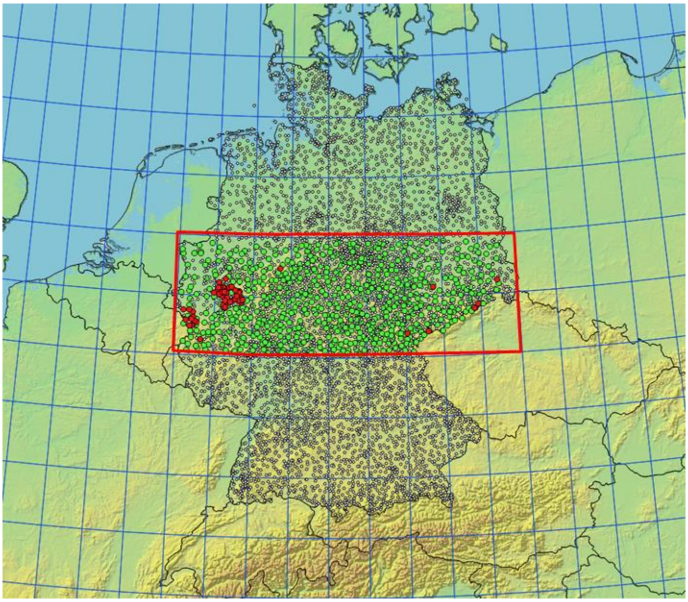


Figure A2.1: Investigation area and precipitation ground stations

2) Database

Records of precipitation, temperature, evaporation and current reservoir conditions (e.g., water levels) are required. In operational mode, the weather service and the reservoir monitoring system must provide these data on a regular basis at predefined intervals.

Seasonal precipitation forecast data is downloaded on a daily basis from NOAA's NCEP coupled forecast system model version 2 (CFSv2)[13]. Since May 2011, NOAA issues seasonal forecasts, consisting of monthly values. Forecasting data is available in a grid format with a resolution of 0.9 degrees. The CFSv2 model covers the whole world and is updated four times a day.

3) Prerequisites

As a first step, a bias correction is performed. Therefore, model output is compared against ground station data and monthly correction factors are derived on the basis of hindcast analyses, starting with data from 2011. First, average rainfall totals for each month were calculated for observation and forecast data. Then, a monthly correction factor was calculated by computing the ratio between the observed and the forecasted values. The correction factors are specific for each ground station. Bias corrected forecasts could then be obtained operationally by multiplying each value of the forecasted time series with the appropriate monthly correction factor.

4) Methodology

As indices have differing inertia and apply to different periods, they can be used for predictive operation. The appropriateness of these indices, the way they should be interpreted and their usefulness regarding early detection of hydrological stress, is tested by conducting hindcast experiments. Indices providing the best skill are selected for conducting forecasts.

For a start, the Standardized Precipitation Index (SPI) was used at all locations. The SPI is recommended by the World Meteorological Organization for meteorological drought monitoring. The SPI can be calculated for different aggregation periods, e.g. only one month or even up to 60 months.

In order to address uncertainty contained in the forecasts, the SPI is calculated for time periods that extend both into the past as well as into the future, thus consisting of different amounts of observed and forecasted values. The performance of indices calculated with different observed and forecasted aggregation periods was compared with results that used only observed values for computing SPIs. In doing so, it is possible to determine how reliable the SPI incorporating forecast data is for different forecast lengths.

[13] http://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2seasonal.shtml

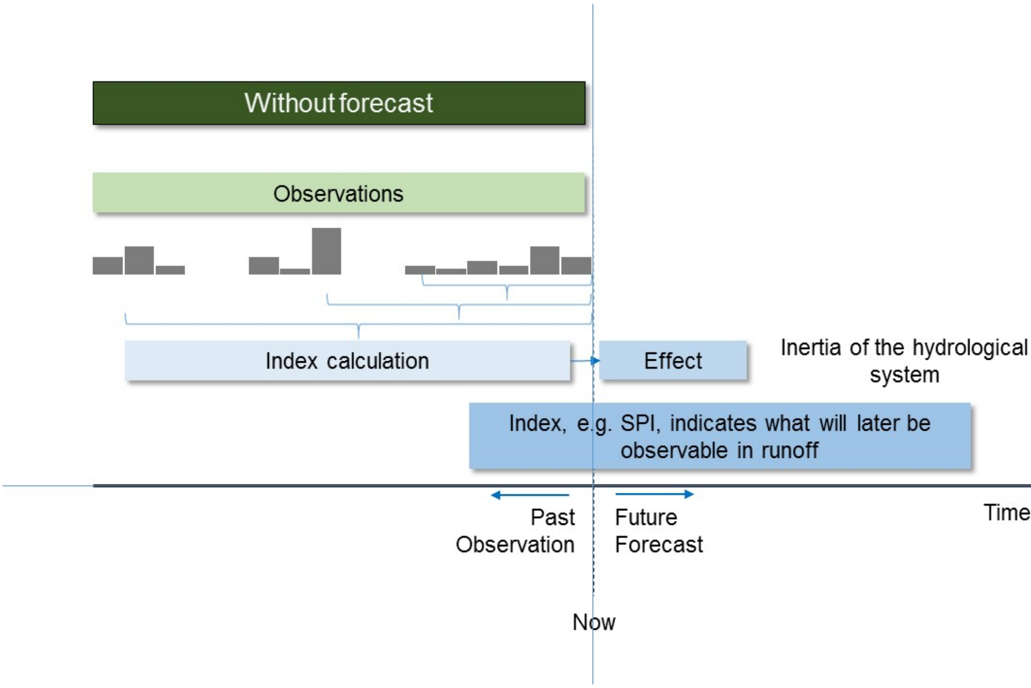


Figure A2.2: Use of indices without forecasts

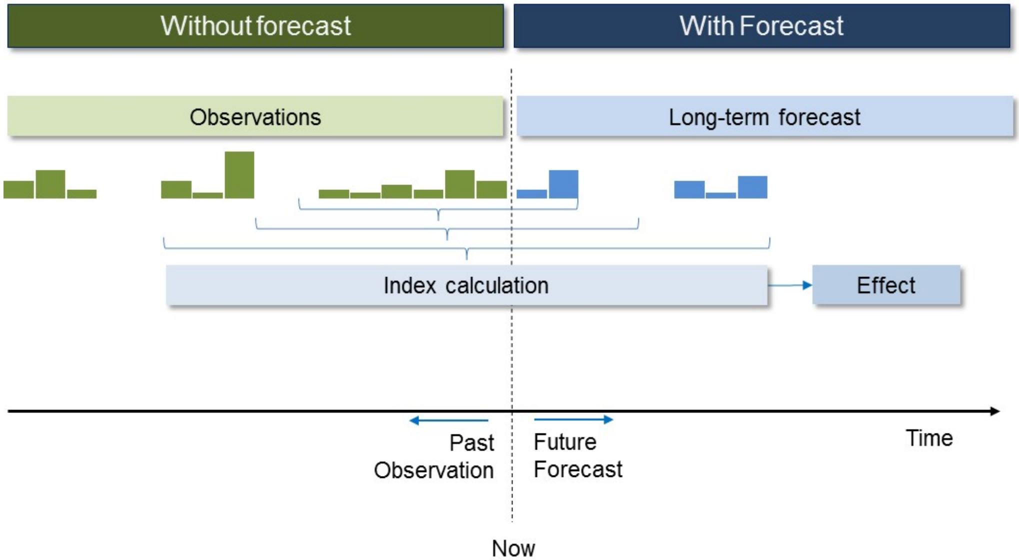
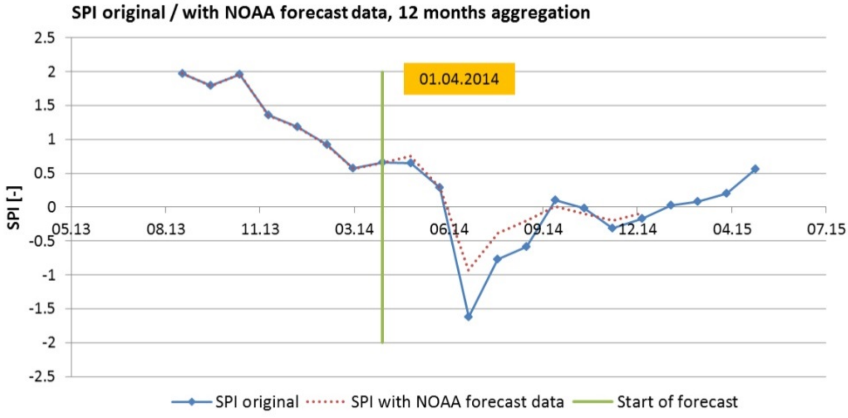


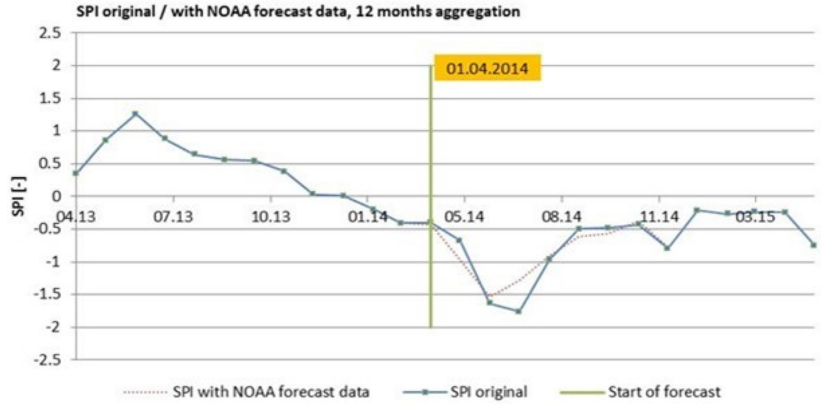
Figure A2.3: Use of indices with seasonal circulation forecasts from NOAA

Calculation of Indices

Based on observed and bias-corrected forecast data, the SPI was calculated for different aggregation periods. The SPI calculated using only observed data ("certain knowledge") was compared with the SPI obtained by considering different fractions of observed records and NOAA forecasts.

Fig 4. shows results for a 12-month aggregation period for three ground stations in eastern Germany. The SPI calculated using NOAA forecasts reveals a good fit in comparison to the SPI based on measured data and more significantly exhibits the same tendency for upcoming dry periods.





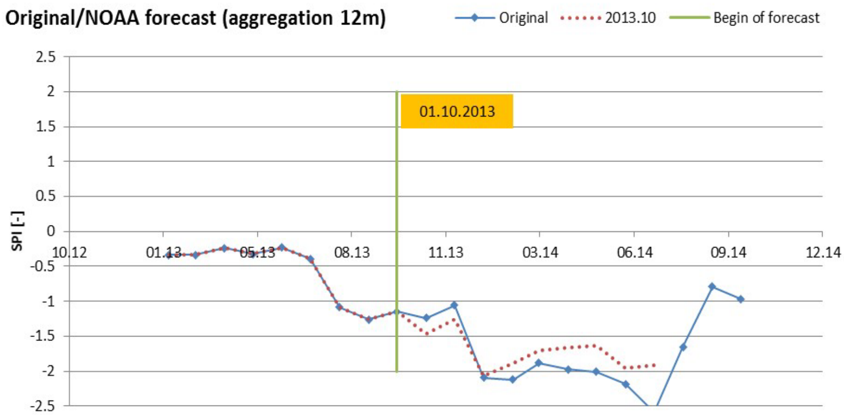


Figure A2.4: SPI calculated with observed / NOAA forecast data, examples from different sites

5) Adaptation of reservoir operation

Once the SPI (or indices in general) is calculated based on combined past and forecasted values, it can be used to adjust operation of reservoirs. Adjustment cannot be established in a general way but requires site-specific rules. However, what can be generalized, is the way in which the results of indices are introduced. First, site-specific operation rules best suited for intervention must be identified. Second, threshold values for indices must be identified for when intervention should be triggered. Third, the aggregation period is highly dependent on the local situation and needs to be determined for each single individual case.

Reservoirs in West-Germany with catchment areas ranging from 250 to 600 km², operated with threshold-based rules, could be improved by using a 9 to 12 month aggregation period and a threshold value of -1.5 (SPI + Evaporation based indices). When the index dropped below -1.5, release rules associated with the next lower storage-threshold level were applied to counter an expected decrease of inflow. This meant a reduction of downstream releases depending on the time of year and current storage volume. Not surprisingly, not all critical periods could be identified by applying this approach. However, two thirds of critical low flow conditions with corresponding low water levels in the reservoirs could be tackled in a timely way. The approach was used without forecasts prior to 2011 and as of 2011 with forecasts to make full use of the observation period with more than 100 years for evaluation.

The figure below indicates the volume of two reservoirs with (blue line) and without (red line) correcting intervention by means of (here) SPI. All yellow sections show SPI less than the threshold value for intervention and with reduction of releases. In other words, during the yellow periods, releases are reduced in order to avoid a further drop of the water level.

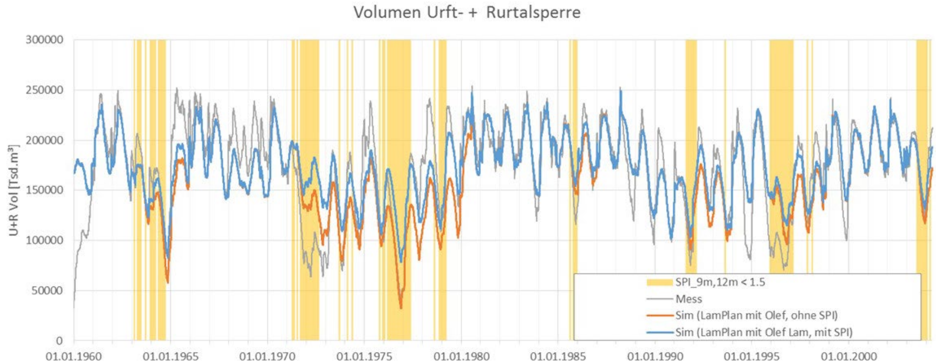


Figure A2.5: Storage volume with/without SPI-based hedging rule (blue=with, red=without)

In Central Germany, a reservoir with a catchment area of less than 50 km² revealed a different pattern. Only aggregation periods longer than 18 months with a threshold value of minus 1.0 showed good results. Shorter aggregation periods or lower threshold values were either not consistent enough or started too late to result in counter measures that took effect. In this case, the target operation rule for intervention was water supply provision. Similar to a hedging rule, water provision was subjected to a quota of a rather small percentage as soon as the index dropped below -1.0 to prevent larger reductions later on. In doing so, the reservoir could be kept above a water level that becomes critical from the viewpoint of water quality.

The initial assumption that the size of a catchment area is a reasonable parameter in order to pre-estimate aggregation periods could not be confirmed. The interplay between climate, the catchment's geology as an indicator for "inertia" (or "hydrological memory") and the reservoir itself seems more complex. As a result, each reservoir or reservoir system must be individually scrutinized to find the best set of aggregation periods and threshold values.

This project is funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, BMUB.

A comparable method, based on direct utilisation of forecasted precipitation instead of hydro-meteorological indices, was tested for the Lower Mekong Basin in 2016 by the Author by order of the Mekong River Commission and GIZ. Results revealed a higher degree of uncertainty and confirm the assumption that indices are more robust.

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A3 - SHORT-TERM SCALE

USE OF RESERVOIR STORAGE FOR FLOOD OPERATION IN THE KUMANO RIVER BASIN – JAPAN

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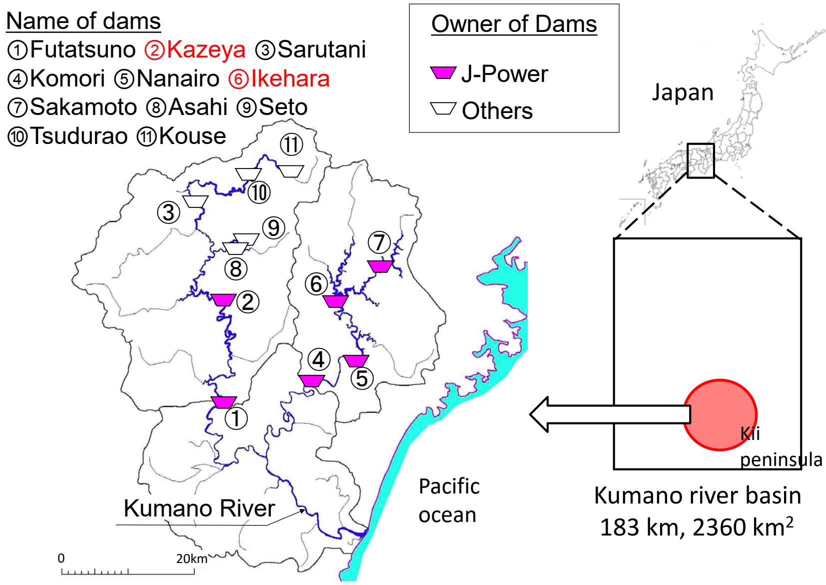
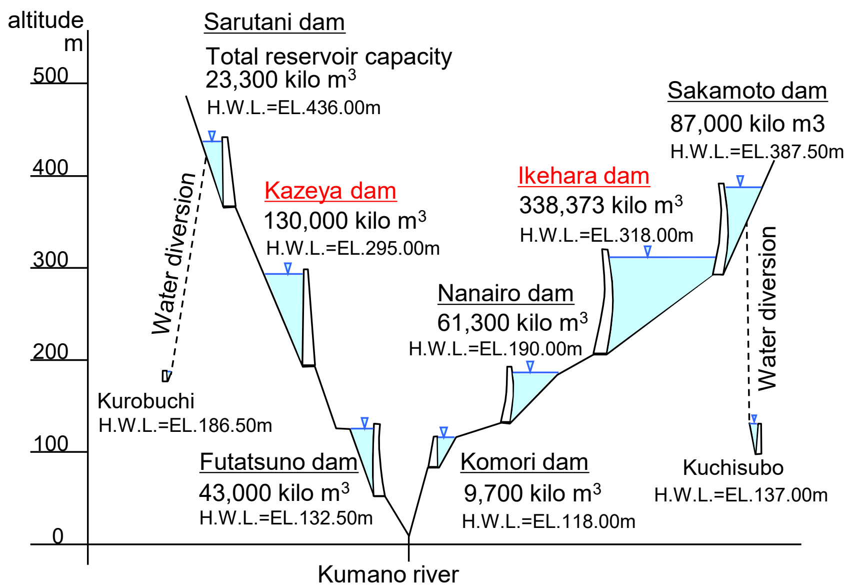
1- Background

Kumano river is located in Kii peninsula at the middle part of Japan along the Pacific Ocean. Its basin spreads almost all in mountain area, namely 97 %, which results in the steep slope of the river bed and much precipitation about 3000 mm per annum. It has (the comment is illegible.) 2360 km^2 drainage area including 18 municipalities with a population of 84000. Many typhoons periodically pass the basin and occasionally bring disaster due to much precipitation. As an example, Typhoon Isewan (category 5) caused huge disaster in the middle part of Japan and 5 fatalities and 2300 inundated houses in the Kumano river basin in 1959.

There are 11 dams for hydropower and irrigation, not for flood protection, in the basin as shown in Figure A3.1. J-Power has been operating 6 hydropower dams in the basin and has contributed to flood mitigation by providing flood storage in reservoirs during the rainy season. Taking the opportunity of the last disaster due to the typhoon No.12 in 2011, the corporative action among the governmental river administrator and J-Power has been commenced for enhancing the flood mitigation using the hydropower dams in the Kumano river basin. Since then J-Power has explored and verified more effective flood mitigation using hydropower dams within the limitation of the commercial operation of the hydropower plants. For this purpose, the study has been conducted on the validity of released meteorological information for the proactive reservoir operation during floods.



(a) Plan

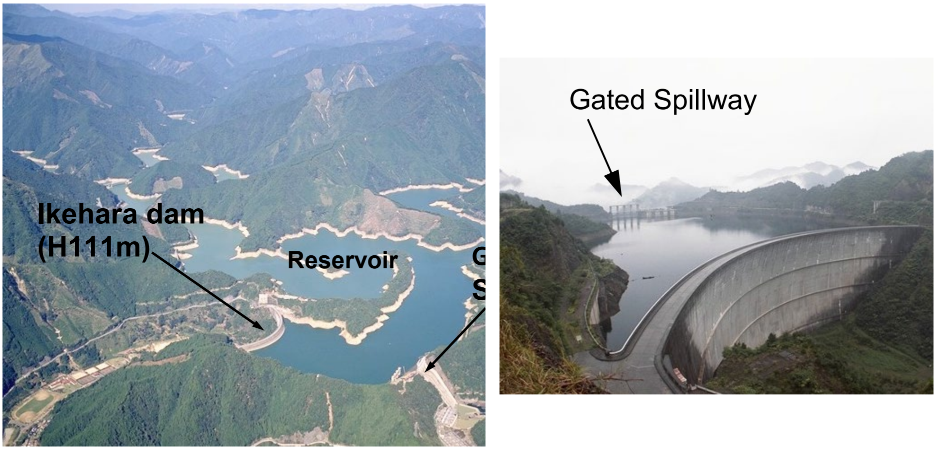


(b) Profile

Figure A3.1 Dams in Kumano river basin

2- Flood risk mitigation using existing hydropower dams

The relatively large reservoirs of Ikehara dam (1964, arch dam, 111 m high) and the Kazeya dam (1960, concrete gravity, 101 m high) are studied for the flood mitigation. The reservoirs are 338 MCM and 130 MCM in volume, respectively. The dams have gated spillway with the maximum discharge of 6700 and 5200 m^3/sec, respectively. The Ikehara dam and its spillway arranged apart from the dam are shown in Figure A3.2.



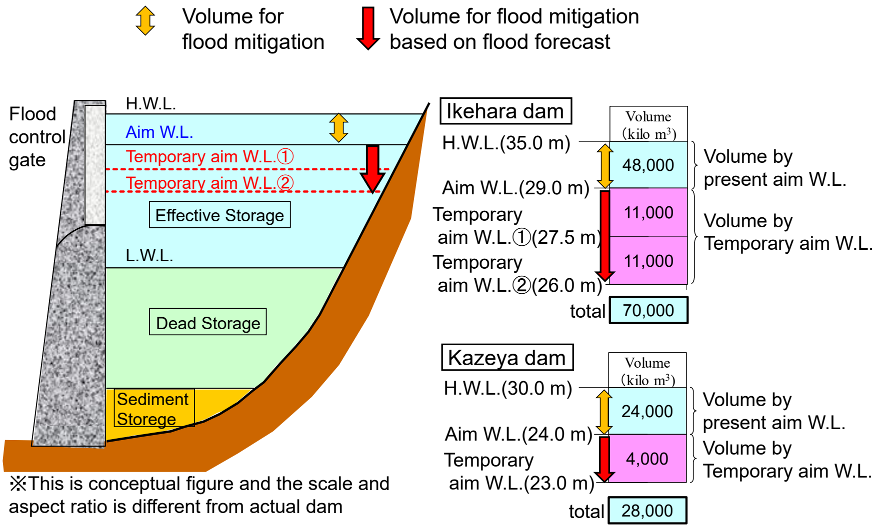
(a) Overview (b) Ikehara dam

Figure A3.2 Ikehara dam and its reservoir

The flood mitigation method for the Ikehara and the Kazeya dams will be conducted by following manner. When the flood caused by much precipitation in the basin is expected, the power generation is conducted in a proactive manner to draw down the reservoir water level to the aim water level from the usual operation water level for providing the reservoir flood storage, as shown in Figure A3.3.

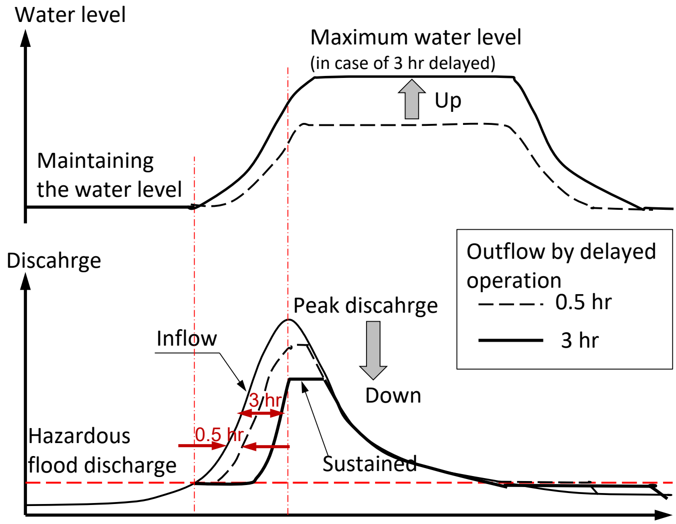
Until the discharge does not exceed the hazardous flood discharge, the spillway gates of the dam are operated to release the flood so as to maintain the aim water level. As increasing the flood discharge more, the gate operation follows the delayed operation rule, of which concept is illustrated in Figure A3.4. To release the flood beyond the hazardous flood discharge, the gate is operated to spill the discharge as much as the flood discharges at specified hours before. The specified hours are referred to as a delayed time. The similar gate operation is continuing until the flood discharge reaches the peak value. Then the gate operation is interrupted until the spilled discharge is the same as much as the flood discharge. As decreasing the flood discharge, the gates are operated so as to spill the discharge equally as much as the flood discharge.

The gate operations for the flood mitigation of Ikehara and Kazeya dams are enhanced by providing increased flood storage of 70 MCM and 9 m water depth, and 28 MCM and 7 m water depth, of which water depths were originally 6 m for both. In Ikehara dam, two options of the aim water level are designated depending on the precipitation intensity. In addition the modified delayed operation rule adopts 3 hours to the delayed time instead of original 0.5 hour, taking the increased reservoir volume above mentioned into consideration. The modified operation may result the higher reservoir water level, but has to be less than the high water level of the reservoir.



Note: The water levels are measured from L.W.L.
Left figure is for Ikehara dams.

Figure A3.3 Flood mitigation scheme



Note: Hazardous flood discharge is defined in each dam independently which possibly cause the harmful impact on the downstream area of the dam.

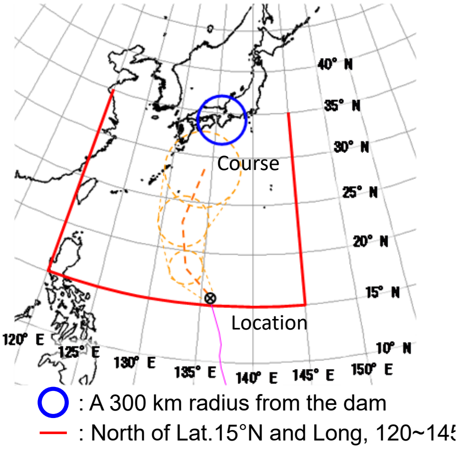
Figure A3.4 Modification of reservoir operation rule

3- Forecast for proactive flood risk mitigation

Reliable meteorological forecasting in a few days advance and its continuous updating are essential for the proactive flood risk mitigation by the reservoir operation following the delayed operation rule above mentioned. The key information is considered as the real-time location and the prediction of the path of the typhoon and the precipitation in the basin, because almost floods have been caused by the typhoons in the Kumano river basin.

Analyzing historical typhoons causing heavy floods in the basin, the typhoons have traveled on the similar paths in the confined area and approached the basin within the 300 km radius, as shown in Figure A3.5. The typhoon information is available in the JMA's （Japan Meteorological Agency）web site which releases the real-time location of the typhoon, its characteristics and predicted path in a few days ahead. The precipitation information by JMA is also available as GPV (Grid Point Value, Figure A3.6) predicted by GSM（Global Spectral Model）. Validating the correlation between the predicted precipitation and the actual ones, 84-hour cumulative precipitation based on the maximum predicted GPV at each 20 km grid in the drainage area of these dams can provide higher correlation to the observed ones. Such prediction is beneficial to provide sufficient time for drawing down the reservoir water level by the generating operation which utilizes the reservoir water effectively.

Reviewing the historical floods again, predicted 84-hour cumulative precipitation above 200 mm caused floods exceeding the specified hazardous discharge of 1500 m^3/s at the dam and triggered delayed operation. Ones more than 500 mm brought severe floods. These can be summarized as the criteria for the proactive draw-down operation of the reservoir for the flood mitigation in Table A3.1.



上記修正

Figure A3.5 Criteria for typhoons as shown in Table A3.1.

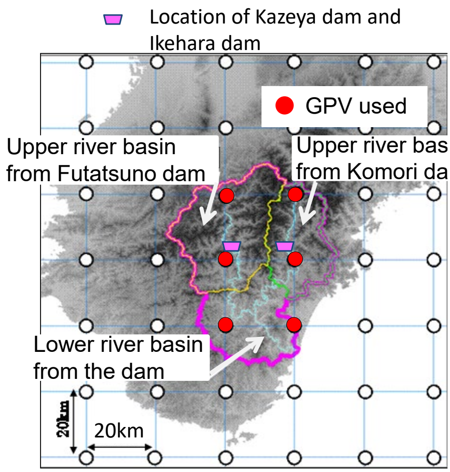


Figure A3.6 GPV locations for the forecast of precipitation in the basin

Table A3.1 Criteria for proactive drawdown operation for flood mitigation

Criteria	Initiation of drawdown	Information	Data update
Location of Typhoon	Shown in Figure A3.5	Real time data	Real time
Predicted course of Typhoon	Within 300 km radius	Forecast in 3 to 5 days ahead by JMA[1)]	3- to 5-hour interval
Predicted rainfall	Cumulative precipitation in 84 hours 200 mm (Severe) 500 mm (Extreme)	84-hour forecast (GSM[2)]) of GPV[3)] by JMA	6-hour interval

1) Japan Meteorological Agency, 2) Global Spectral Model, 3) Grid Point Value

4- Verification

The modified reservoir operation and proactive draw-down criteria shown in Figures A3.3 and A3.4 and Table A3.1 are validated in terms of the efficiency of the flood mitigation by the examination of the historical floods.

Firstly, the relation between the draw-down criteria shown in Table A3.1 and the observed discharge at the dam is examined on the occasion of the historical 329 typhoons passed through the middle of Japan. When a typhoon meeting all criteria would cause the flood exceeding the specified hazardous flood discharge at the dam, it will be the right case. Otherwise will be the wrong case. The results are summarized in Table A3.2. Half cases which satisfy the criteria and almost all cases which fail the criteria are identified as the right cases. It clarifies that the criteria are practical ones in order to identify the necessity of the draw-down of the reservoir.

Table A3.2 Verification of the criteria of drawdown operation

Evaluation	**Number of typhoons**	
	Above the hazardous flood discharge (1500 m^3/s)	Below the hazardous flood discharge (1500 m^3/s)
Satisfy the criteria	16 (Right)	14 (Wrong)
Fail the criteria	1 (Wrong)	298 (Right)

Secondary, the effectiveness of the delayed operation is examined by the simulation of the operation in the Ikehara reservoir (refer to Figure A3.3) under the following assumption.

1) Initial reservoir level is 29 m as the water level in the rainy season.

2) When the situation of the typhoon satisfy the criteria shown in Table A3.1, the reservoir water level is proactively draw down by the generation with the discharge of 342 m^3/s.

3) The flood is controlled firstly by the gate operation to maintain the reservoir water level.

4) As increasing the discharge, once the discharge at the dam exceeds the hazardous discharge of 1500 m^3/s, the gate operation following the delayed operation rule is commenced to regulate the flood.

The simulated results are shown in solid lines in Figure A3.7. The cumulative precipitation in an 84-hour specified as the criteria are 200 mm and 500 mm for Case A and Case B, respectively. The moment of satisfying the draw-down criteria and its initiation is shown in vertical dotted lines. These show that the sufficient times are ensured for the reservoir draw-down to the specified water level in both cases. Due to the flood characteristic of shorter flooding duration less than the delayed time of 3 hours in Case A, the maximum discharge at the dam does not exceed the hazardous discharge of 1500 m^3/s. Contrary, one for

Case B results 1708 m^3/s by the delayed operation which follows the increasing flood discharge with specified delayed time. Both are less than the maximum of the natural flood discharge. The reservoir levels in both cases stay under the specified one. In the actual figure in Case B, the actual discharge was a few of 326 m^3/s because the initial water level in low of 10 m and the gate operation was withheld by utilizing the vacant reservoir volume.

5- Conclusions

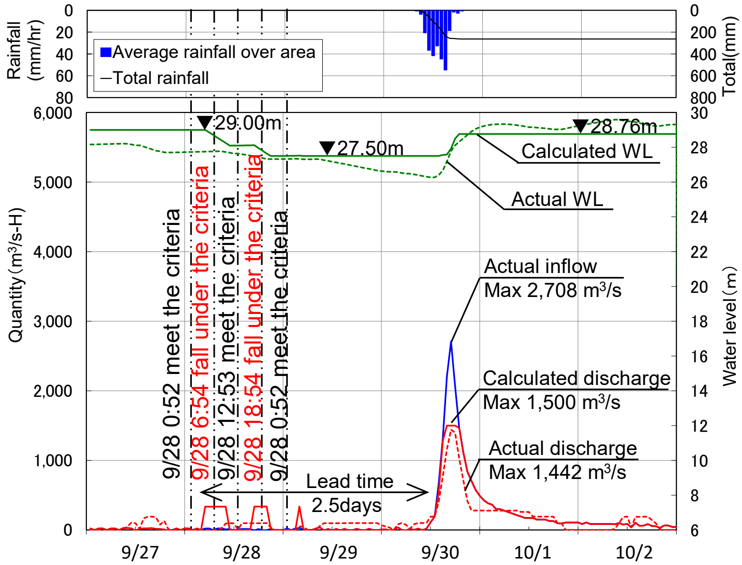
The flood risk mitigation using the hydropower dams by the proactive reservoir draw-down and the modified reservoir operation method by effective use of the resultant vacant reservoir volume are examined. The following conclusions are obtained.

1) The meteorological information of the location and the path of the typhoon and the precipitation prediction using GSM released by JMA are effective index for the proactive reservoir draw-down for the flood mitigation in the Kumano River basin. These characteristic of easy access and frequent updating are adequate for the reservoir operation criteria.

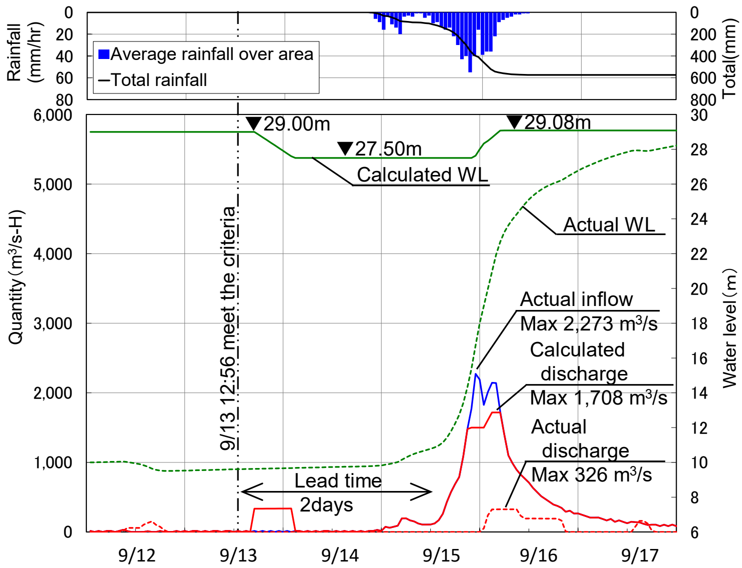
2) The specified criteria for the proactive reservoir draw-down provides sufficient time for reservoir draw-down using the generation discharge.

3) The modified reservoir operation method comprising the delayed operation concept are verified to be practical ones for the studied dam by the flood routing simulation on historical typhoon cases.

The studied method has been actually applied for the reservoir operation since 2012 at the basin. Further validation will be conducted based on the consequences.



(a) Case A: Typhoon No.17 in 2013



(b) Case B: Typhoon No.18 in 2013

Figure A3.7 Simulation of the Ikehara reservoir operation

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(1) Takakura H., Matsubara T., Nakakita E., Takada N.: Study on validity of the hydroelectric dam operation adopted GSM and the information about typhoons, 85th ICOLD annual meeting, Prague, Czech Republic, 2017.6

(2) Matsubara T., Kasahara S., Shimada Y., Nakakita E., Tsuchida K., Takada N.: Study on applicability of information of typhoons and GSM (Global spectral model) for dam operation), Journal of Japan Society of Civil Engineers, Sr. B1 (Hydraulic Engineering), Volume 69(4), pp. I-367-372, 2013(in Japanese)