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Managing Climate Risk in Water Supply Systems

Edited by Casey Brown and M. Neil Ward

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The first version of these materials was part of a suite of resources developed through the IRI network to share climate risk knowledge related to a range of sectors and climate-related problems. In turn, they were viewed as part of an emerging global resource to support climate risk management. The materials have been updated and adapted for this book. The intended primary audience of this document is technical professionals in water resources management. The scope is illustrative of climate risk management techniques and examples for water supply systems, and in addition, the materials are intended to also illustrate concepts relevant to managing risks in other areas of water resources management. The purpose is to have an educationally motivated text with accompanying practical exercises that can be consulted alone or in support of a learning event (e.g., a workshop or a course). It is intended to raise awareness of risk management opportunities based on the established science of today, and to stimulate readers and workshop participants to consider options and analyses that will highlight opportunities for better management in the water systems in which they are stakeholders.

The concepts and approaches described in this document have accumulated through a large community of research and are illustrated in the text by a range of examples. Quantitative examples and practical exercises here particularly draw upon the outputs of a project on climate risk management approaches for the Angat Reservoir in Philippines. This work was undertaken by the International Research Institute for Climate and Society (IRI), in partnership with: Institute for Strategic Planning and Policy Studies (ISPPS), College of Public Affairs at the University of the Philippines – Los Baños; National Water Resources Board (NWRB); Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA); Metropolitan Waterworks and Sewerage System (MWSS); National Power Corporation (NPC); Manila Water Company, Inc.

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These materials were prepared by Casey Brown[1], Kye Mesa Baroang, Esther Conrad, Bradfield Lyon, David Watkins[2], Francesco Fiondella, Yasir Kaheil[3], Andrew Robertson, Jason Rodriguez, Megan Sheremata, and Neil Ward. Valuable comments and input were provided by Upmanu Lall, Shiv Someshwar, Paul Block, Mohammed Boulahya, Stephen Zebiak, Molly Hellmuth, Agnes Rola, Dulce Elazagui, Jessica Bolson, Willem Landman, Shahbaz Mushtaq, Alan Hamlet, and Yonas Ghile

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About this Manual

A PRACTICAL APPROACH TO TRAINING

This manual has been developed as a learning tool and can be used with a companion series of practical exercises. They have been developed to provide a hands-on approach to learning key concepts in hydrology and climate science as they relate to climate risk management in water supply systems, as introduced in the text. These exercises are located online, and are available in CD-ROM format. They are intended for use with Excel 2003 or a later version.

Please go to http://crk.iri.columbia.edu/water/ for complete exercise files.

Theses practical exercises involving quantitative analysis have been developed to illustrate and teach some of the key concepts introduced in the text. The content of the exercises is outlined below.

Exercise 1: Sizing a reservoir and constructing yield-reliability curves using climate information

Exercise 1 provides the information and skills necessary to develop a reservoir yield-reliability curve and understand how it is affected by changes in water demand or inflow. After examining how inflows and demand affect storage requirements for a reservoir, the participant creates a curve that tracks the reliability based on changing yields for a reservoir with a given capacity. The exercise also allows the participant to explore the impact of climate conditions on inflow and reliability. This promotes understanding of how seasonal climate information can be used to determine the necessary size of a reservoir and the expected reservoir reliability.

Exercise 2: Developing a statistical seasonal inflow forecast model

Exercise 2 allows the participant to create and validate a statistical model to forecast a three-month seasonal inflow based on hydroclimatic data. The participant uses relevant climate, inflow and reservoir data for a specific reservoir. The exercise illustrates how to choose an appropriate predictor variable and determine the level of skill that can be expected when applying the statistical forecast model. The participant is able to vary the climate predictor value (antecedent conditions or an ENSO index) and observe how this affects the model's forecast output.

Exercise 3: Assessing risk for a multipurpose reservoir using a water allocation scheme and simulated inflows

Exercise 3 broadens the scope of risk assessment beyond simple reliability analysis based on the historical record. The participant considers a realistic set of reservoir operating rules and makes water allocation decisions. The exercise then applies stochastic modeling to simulate various future seasonal inflow scenarios over a 40-year period. This allows the participant to examine the potential effects of multidecadal climate variability and/or long-term trends on the system reliability. The exercise also includes a module that illustrates the possible economic consequences of water supply shortfalls.

Exercise 4: Integrating seasonal forecast information into reliability analysis for a multipurpose reservoir

Exercise 4 builds off previous exercises to demonstrate how the probabilistic seasonal inflow forecast developed in Exercise 2 can be applied to historical conditions and used to determine expected reliability for a multipurpose reservoir. The participant is able to construct a seasonal inflow forecast, use it as an input in a stylized decision support model, and observe how changes in water allocation can affect the expected reliability. The exercise also provides the observed inflow from the historical record as a point of comparison for the forecasted inflow.

Exercise 5: Managing risks and opportunities for a multipurpose reservoir within an institutional context

Exercise 5 is intended to be conducted in groups. It includes a role-playing component that separates participants into different stakeholder groups and provides guidance for making decisions within a simulated institutional context. The exercise allows the participants to make water allocations for a multipurpose reservoir using a retroactive forecast based on a climate-based probabilistic seasonal inflow model. The participants can then assume the season elapses and update the model using observed inflows from the historical record. Participants are able to both explore the dynamics involved in making decisions using probabilistic forecasts and recognize the possible consequences of these decisions.

Chapter 1

Introduction

INTRODUCTION

Water resources systems provide multiple services and, if managed properly, can contribute significantly to social well-being and economic growth. However, extreme or unexpected hydroclimatic conditions, such as droughts and floods, can adversely affect or even completely interrupt these services. Severe social, economic and ecological impacts may result when societies are unable to predict, adapt to, or respond to these conditions. This manual seeks to provide knowledge, resources and techniques for water resources professionals to manage the risks and opportunities arising from **hydroclimatic variability** and **change**.

CLIMATE AND WATER RESOURCES MANAGEMENT

A primary objective of this manual is to provide the tools and knowledge necessary to improve traditional **risk management** approaches in the water resources sector by integrating innovations and developments in the understanding of global and regional climate systems. Traditionally, regulation plans for water resources systems have been based entirely, or almost entirely, on the historical hydrologic record. For example, studies continue to rely on **critical period hydrology** (Hall & Dracup, 1970), in which managers determine a **firm yield** of a system based on **system reliability** when confronted with the **worst drought on record**. In general, decision making during less severe droughts is heuristic (informal) and lacks explicit consideration of risk, instead depending primarily on past experience, observation of current conditions, and professional judgment (Lee, 1999).

One of the weaknesses of such traditional approaches is that they do not typically address changes or **variability** over longer time scales in the water system. Changes in population, land use and climate, among others, can result in changes to the system that lead to outcomes significantly different from the **observed historical record**. Additionally, traditional approaches rarely utilize recent advances in the understanding of the climate system or the resulting improvements in the ability to predict climate across various time scales. Importantly, much of **hydrologic variability** is driven by dynamics in the climate. **Climate variability and change** occurs across multiple time scales (see Figure 1.1) and affects water resources decision making on a range of **decision horizons**. For example, a flood may occur over a period of hours, whereas a drought may unfold over a period of months or years. The effects of such events can be impacted by decisions made at both the operational and planning levels.

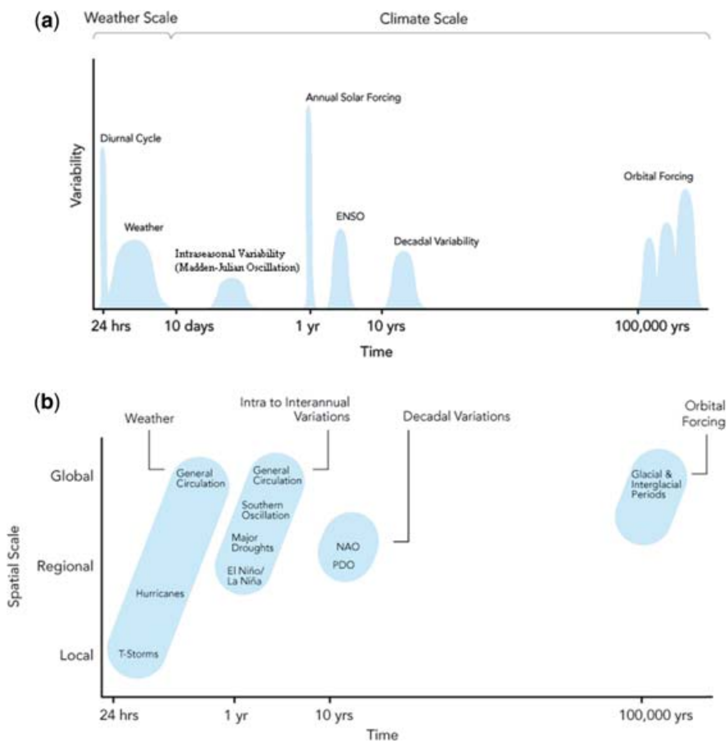

Figure 1.1 Characteristic time and spatial scales of aspects of the climate system. Panel (a) illustrates various elements of weather and climate variability, ranging from changes from day to night (diurnal cycle) to the effects of changes in the orbit of the Earth and other celestial bodies (orbital forcing). The width of each blue distribution shows the timescale over which the associated forcing impacts the climate system. The height indicates the degree of variability (e.g. seasonal changes, or annual solar forcing, are typically much greater than changes in day-to-day weather within a season). Note that this diagram is intended to be schematic and should not be interpreted quantitatively. Panel (b) provides some examples of events or patterns that manifest at each timescale, as well as a generalization of the spatial scale over which their impacts are felt. For example, droughts occur over multiple months and generally have physical impacts at a regional scale. Thunderstorms, however, occur at the timescale of hours and days, and operate at a smaller spatial scale (local level).

As awareness of longer-term climate variability (e.g. **decadal variability** and **multidecadal variability**) and the potential effects of global climate change increases, water managers are increasingly motivated to implement policies for risk-based decision making. Fortunately, the growing awareness is accompanied by improvements in tools for both **forecasting** climate and using that climate information in managing water resources.

FORECASTING CLIMATE AND INFLOWS

Climate scientists have made significant progress in the ability to understand and predict the climate on **seasonal** to **interannual** time scales. They are also rapidly advancing **climate models** that support **projections** of long-term **anthropogenic climate change**. All of these are relevant to water resources managers. This manual examines some of the basic science and techniques used in the predictions. For example, one of the key aspects of **seasonal climate variability** for many regions of the world is the **El Niño-Southern Oscillation (ENSO) phenomenon**. As explained in more detail in Chapter 3, the ENSO phenomenon is manifested as phases called El Niño, La Niña or neutral, which are characterized by different impacts on regional climate (see Figure 1.2).

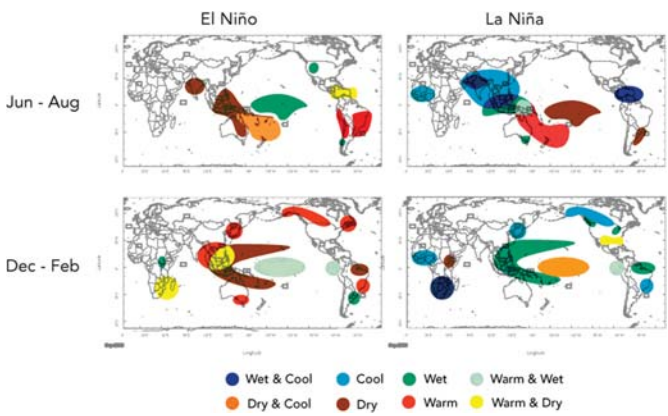

Figure 1.2 Temperature and rainfall conditions associated with the El Niño-Southern Oscillation phenomenon during El Niño and La Niña events.
Source: Adapted from NOAA Climate Prediction Center.

Forecasts of ENSO conditions and related phenomena can often provide information on probable precipitation conditions months, or even seasons, in advance. Given the appropriate tools and information, these precipitation forecasts may also be able to be translated into streamflow forecasts for certain water systems. This information can, in turn, enable water resources managers to better predict reservoir inflows, possibly offering significant improvements over using only historical inflow records. This manual explores how the appropriate use of climate forecasts at seasonal and other time scales may be able to improve water management under current conditions, as well as help systems adapt to changing conditions.

It is also important to recognize some of the limitations of climate forecasting. In many cases, the skill of the climate forecast may not be sufficient for operational use, due to inherent physical **predictability** limits of regional climate or limited knowledge of climate processes and modeling capabilities. Additionally, institutional barriers to the use of climate forecasts may exist, and water managers may be hesitant to apply new methods that could expose them to greater liability. Because of the possible benefits from using climate information, innovative tools and management strategies should be developed to handle the complexity involved in using forecasts. This manual describes some of these tools and presents a robust approach to **climate risk management**.

USING CLIMATE INFORMATION TO MANAGE CLIMATE RISKS AND OPPORTUNITIES

Climate variability and change can offer an array of both risks and opportunities for water resources systems. Managers are responsible for minimizing the risks while maximizing the benefits of a system. The distribution of negative outcomes relative to opportunities is typically quite uneven, particularly if a system is managed well (Figure 1.3).

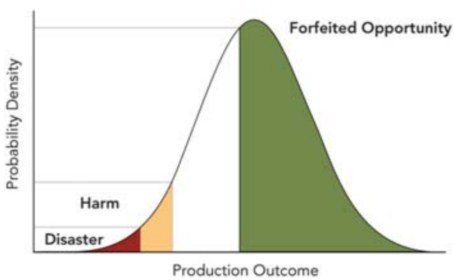

Figure 1.3 Normal distribution of outcomes.
Stylized representation of a range of possible outcomes (such as crop yield) following a normal distribution (bell curve). There exists an outcome below which the system faces some degree of harm or, if the outcome is even more extreme, a disaster. The white space to the right of the 'Harm' threshold can be considered baseline outcomes (i.e. outcomes that result in neither harms nor benefits). An individual outcome leading to a harm or disaster has lower probability than an outcome resulting in baseline conditions. The green area represents possible benefits from the climate conditions. If a system is managed only to avoid harm or disaster, these benefits may not be enjoyed and could be considered forfeited opportunities. *Source:* Adapted from Brown and Hansen (2008).

Although climate information is only one input in the decision-making process, it can have a significant effect on the outcomes for a water system. This manual outlines a three-step approach to using improved climate information and forecasts to manage climate risks and opportunities. Chapter 5 describes the recommended process, which begins by assessing the hydroclimatic risk for the system. This includes examining the existing climate challenges and the system's sensitivity to climatic changes and variability. The water manager may collaborate with relevant climate professionals, national meteorological agencies and other related institutions as needed, to develop probabilistic climate predictions and projections across time scales. These predictions can help narrow the range of likely climate futures. The creation of such information through collaboration is an important step in the emerging concept of modern climate services (World Climate Conference 3, 2009). Finally, water resources managers can use this information to determine a portfolio of options to address the specific hydroclimatic risks to the system.

Ultimately, successful climate risk management relies on 1) the quality of the climate information; 2) successful integration of this information into relevant decision tools (such as reservoir models); and 3) incorporation of the information into decision making, including relevant policies, regulations, and other institutional processes. Therefore, it is critical to understand the institutional and policy context in which climate information is to be used.

INSTITUTIONAL ASPECTS OF MANAGING CLIMATE RISKS AND OPPORTUNITIES

Water management policies and institutions must address a complex set of interconnected problems. Water resources are variable across time and space, and are typically shared across multiple users with differing needs. While agriculture typically consumes the greatest proportion of water, population growth, urban development and industrialization are resulting in a steady increase in demand for municipal and industrial water use. Water use for environmental management has also emerged as an important consideration in many settings. It is in the context of these increasing pressures over the past several decades that the **integrated water resources management (IWRM)** approach emerged. IWRM recognizes the need to balance economic efficiency, social equity, and environmental sustainability in a holistic approach to water resources management (Lenton & Muller, 2009).

Water policies and associated regulations provide formal guidance to water resources decision making, typically by outlining priorities for water use, defining criteria for water allocation, and establishing a process for decision making. In addition to understanding their content, it is also important to recognize that these policies emerge in a particular historical and socio-economic context. Policies and regulations are shaped by certain attitudes toward risk and, quite often, differing degrees of political influence by various users. Competition and other conditions within an industry can also, in some instances, provide a disincentive for acknowledging the use of climate information in water management practices. Regardless of the quality of climate information, such factors will continue to play an important role in decision making.

In addition to formal water policies, informal institutional arrangements are equally crucial. North (1990) defined informal institutions as customary but unwritten modes of interaction, and he argued that these often play an even more important role in actual decision outcomes – and eventually, overall economic performance – than do formal policies. Informal institutions might include everything from the existence of an informal committee that meets regularly to discuss water allocation, to cultural norms that lead to hierarchical decision-making patterns. Whether or not a climate risk management approach is successfully implemented depends significantly upon whether or not it integrates well with existing informal institutions.

In the context of a changing climate as well as continuing demographic and land use changes, anticipatory, **risk-based decision making** is becoming increasingly important. Approaches such as integrated water resources management, which explicitly acknowledge the interconnectedness of problems across multiple sectors and scales, are generally well-suited to accommodate this. However, achieving this may require changing institutional arrangements, which are often better equipped to respond to impacts after they occur than they are to anticipate and manage risks (Someshwar, 2008). An understanding of current formal and informal institutional arrangements, including an analysis of relevant stakeholder institutions, can help identify both attitudes toward risk, needs and priorities of various water users, as well as key informal institutions that help shape outcomes, laying the groundwork for effective climate risk management approaches.

CONCLUDING REMARKS

Our intent is to provide a foundation for water resources professionals to understand how to use climate information and forecasts to manage hydroclimatic risk and take advantage of opportunities. In practice, this is a dynamic process that must be done in close collaboration with climate scientists, relevant meteorological agencies, policy makers and other stakeholders involved in managing a water system. Ultimately, this manual should help guide water resources managers to engage in dialogue with relevant partners and understand the appropriate questions to ask. Our approach is to encourage "learning rather than knowing, the difference being that the former emphasizes the process of exchange between decision makers and scientists, constantly evolving in an iterative fashion rather than aiming for a one-time-only completed product and structural permanence" (Feldman & Ingram, 2009). To facilitate that process, this manual aims to support water resources professionals to:

- Understand limitations of traditional approaches to water management and opportunities for improvement based on new understanding of climate;

- Recognize the scales of climate variability and change and their impact on water systems;
- Understand the basic mechanics of a simple seasonal forecast model;
- Improve operations tools, such as rule curves, by utilizing climate forecasts;
- Evaluate the expected benefits and risks of forecasts, including in the context of a changing background climate;
- Conduct a basic climate risk assessment;
- Become familiar with market-based tools and other innovative approaches that can mitigate climate risk; and
- Understand important institutional aspects of climate risk management.

Although the manual focuses primarily on reservoir management, much of the information and many of the concepts are widely applicable in the broader water resources field. Managing water supply in reservoir systems provides a context in which to explain the techniques and knowledge necessary to develop a climate risk management approach. However, the skills involved in understanding how climate variability and change affect a system and recognizing how best to translate that understanding into strategic anticipatory action are transferable globally and across disciplines.

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Chapter 2

Water resources analysis and management

INTRODUCTION

Water resources management is centrally concerned with understanding the variability of water resources and using that knowledge to control water availability to provide benefits to society. This requires techniques to measure the various elements (e.g. precipitation, evaporation, runoff) in a hydrologic system that lead to changes in the water availability across multiple time scales[1]. Underlying patterns of climate variability contribute to hydrologic variability, while longer-term trends can generally be understood as leading to fundamental changes to the system. Due to limitations in data availability, modeling capability, and comprehension of physical processes, there remains considerable uncertainty in understanding and predicting hydrologic variability and change. Thus, while this chapter presents some techniques for hydrologic analysis, these must be accompanied by tools to address the possible risks. Chapter 5 builds off these techniques and climate-related tools to provide a framework for climate risk management.

A system without any **trends** or changes to the long-term **historical hydrologic variability** is known as exhibiting **stationarity**. In such systems, statistical tests can confirm stationarity and historical hydrologic records may be appropriate to use in planning studies. However, few systems exhibit this trait, and even when the hydrologic variability appears consistent, this provides no guarantee against current or future changes which might negate the assumption of stationarity. Some important factors to consider include land use change, decadal climate variability not observed in the record, and long-term climate change. As an example, the number and intensity of tropical storms in the Atlantic Ocean appear to fluctuate on a cycle of approximately 20–40 years. If one had only a short record of these storms, the possible multidecadal cycle might not be apparent; the

[1]It is also critical to understand water demand and how it is expected to change. While that is not the focus of this manual, Appendix 2 provides a brief introduction to some of the relevant principles and techniques.

record could appear as stationary (though biased high or low) or exhibiting a significant upward or downward trend (Goldenberg *et al.* 2001).

Regardless of the source of cycles or changes, water resources managers must learn to identify hydrologic variability and change in order to predict future water availability and develop methods of controlling the flow and availability to accommodate society's needs. Storage reservoirs represent one of the most common and critical methods of managing hydrologic variability. Reservoir management generally involves two separate, but overlapping, areas of expertise and decision making: planning and operations. The decisions made by both planning and operations professionals require detailed knowledge of the given watershed, which generally includes physical properties as well as historical streamflow information.

Additionally, while not always adequately considered, climate information, including both historical records and forecasting techniques, is critical for the effective management of hydrologic variability and change. This chapter examines various traditional approaches to predicting and managing water availability in storage reservoirs. The discussion examines the crucial role of climate variability in water resources management and the need to explicitly integrate climate information into management practices.

Section 1: Predicting water availability

In order to manage water availability, we must first understand the variability of the supply and develop methods for predicting how much water will actually be available. While the following discussion is not exhaustive, it provides some of the fundamental methods for predicting water availability along with an examination of the existing and possible future role of climate information.

Section 1.1: Predicting water availability for unregulated (natural) flow

To predict future water availability for a given system, it is essential to understand the behavior of the system in the past and determine the historical streamflow. This information can then form the foundation for modeling the **unregulated system** and making predictions for future flows, provided the assumption of stationarity is addressed and amended if necessary.

Flow-duration curves

Time series graphs are useful for visualizing the variability of past streamflow. For example, Figure 2.1 shows monthly flows on the Chagres River in Panama. These flows are considered "natural", with no effects of regulation by **storage** or **diversion**.[2]

[2] In the case shown, unregulated flows are estimates of "naturalized" flows based on observed, regulated flows with the effects of storage and diversions removed using a simulation model.

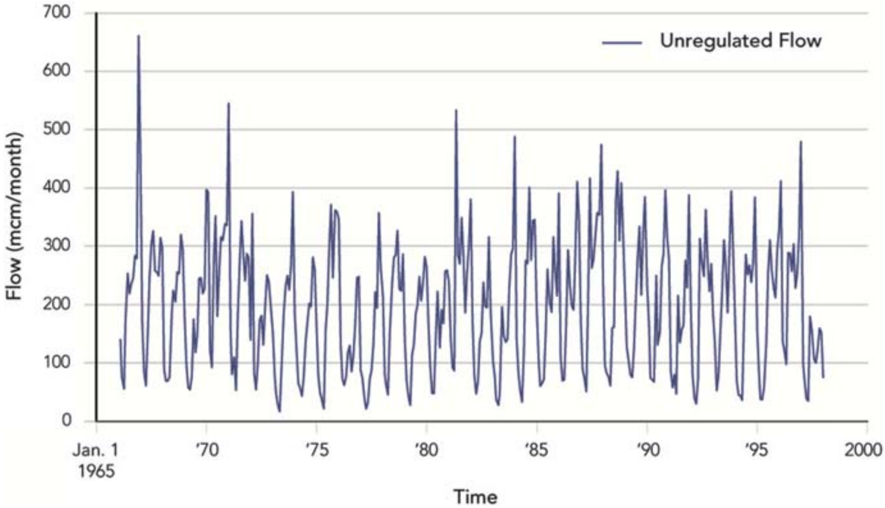

Figure 2.1 Time series of monthly natural (unregulated) flows on the Chagres River, Panama.
The graph illustrates the significant variability of the flow both within a year and between years. Units of flow are million cubic meters (mcm) per month. *Data source:* USACE (2000).

The time series graph reveals the critical importance of climate variability in streamflow across multiple scales. There is a distinct seasonal pattern as well as significant interannual variability. In addition, one can observe persistent drier periods in the early to mid-1970s and again beginning in 1997–98. Such graphs help visualize patterns and trends in the streamflow that might be connected with similar variability in precipitation and the climate. This information is necessary for understanding possible future scenarios and can help guide prediction of water availability.

Another useful way to analyze streamflow data is by plotting a **flow-duration curve** (or exceedance probability curve) which indicates the probability of the flow exceeding a given value. This is done by ranking the data from largest to smallest and assigning an **exceedance probability**, *P*, to each value according to the following formula:

$$P = \frac{m}{n+1} \qquad \text{(Eq. 2.1)}$$

where m is the rank of the data value ($m = 1$ being the largest), and n is the total number of data points.

Flow-duration curves can be useful for decision making because they reveal the likelihood that certain critical threshold flows will be exceeded. Figure 2.2 shows a flow-duration curve for the unregulated Chagres River flows.

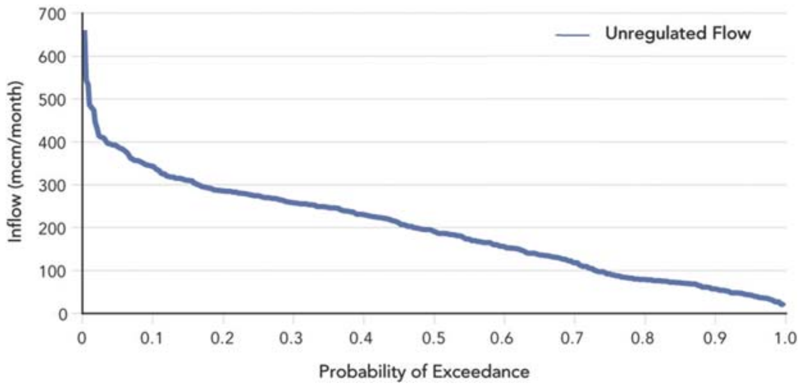

Figure 2.2 Flow-duration (exceedance probability) curve for unregulated monthly flows on the Chagres River, Panama from 1966–1997.
Note that the probability of exceeding a monthly inflow of 400 mcm or more rises steeply, suggesting that such high inflows are increasingly rare. Units of flow are million cubic meters (mcm) per month. *Data source:* USACE (2000).

The nonlinear nature of the flow-duration curve shown in Figure 2.2 is typical for these graphs since the distribution of possible streamflows often follows a near-normal pattern, with extreme high and low flows for each system having very small probabilities.

Flow-duration curves may also be used to understand the results of climate patterns and trends, such as those possibly observed in the time series analysis. For example, the El Niño-Sothern Oscillation (ENSO) phenomenon (introduced in Chapter 1 and described in more detail in Chapter 3) can have significant impacts on climate conditions in various parts of the world. Using flow-duration curves for different phases of ENSO can reveal whether a given system is affected by ENSO-induced changes in the climate conditions (e.g. the cool phase of ENSO over the equatorial Pacific may result in wetter conditions, increasing flows and shifting the curve higher). Figure 2.3 demonstrates the impact of ENSO phases on inflow to a reservoir.

In addition to these types of impacts, Chapters 3 and 4 explore other aspects of climate variability and methods of using climate information to improve forecasts of hydrologic variables. The variability in flows also illustrates the need for ways to use this improved understanding of climate to better manage the risk and opportunities. These concepts are examined further in Chapters 5 and 6.

Watershed modeling

Time series and flow-duration curves illustrate data from the historical record and can be useful for understanding the possible range of future flows. However, predicting future unregulated flows for a watershed or river basin requires the development of a model and knowledge of relevant indicators. Such prediction often requires a computer model representing the key hydrologic processes occurring in the watershed. These models can range from very simple (e.g. a linear regression between precipitation and streamflow) to very complex (e.g. a **distributed, physically-based watershed model**). Most models applied in practice are fairly simple, due to limited data, and combine empirical methods with physically-based modeling.

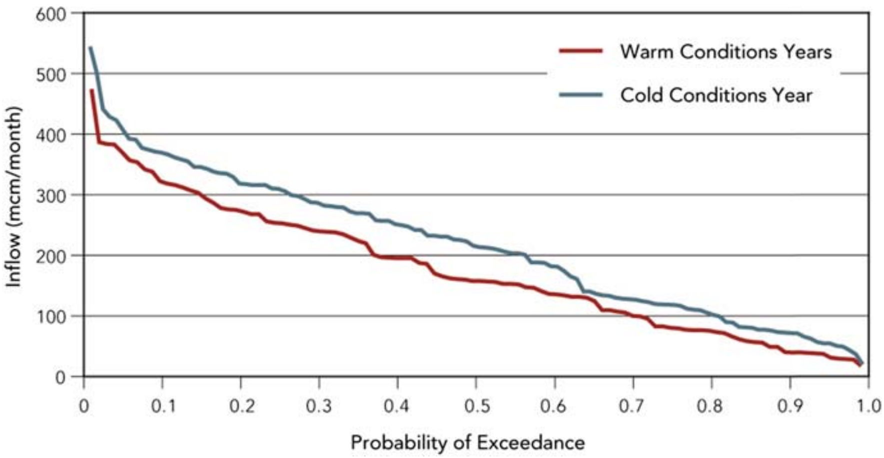

Figure 2.3 Flow-duration curves for unregulated flows on the Chagres River, Panama from 1950–1997.

The red curve shows flow following warm conditions in the Equatorial Pacific during July to September (i.e. El Niño conditions). This is contrasted with the blue curve, which shows flow following cold conditions in the Equatorial Pacific (La Niña). The figure illustrates that for this system, El Niño conditions are associated with lower inflows, while La Niña conditions are associated with higher inflows. Units of flow are million cubic meters (mcm) per month. *Source:* Chagres River data, USACE (2000); SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004).

Physically-based models

Almost all physically-based models use all or a sub-set of the hydrologic processes shown in Figure 2.4.

Physically-based models involve the basic concept of a water budget in relation to these hydrologic processes. For example, a surface water budget may be represented by the following equation:

$$\Delta S = P - I - ET - R \quad \text{(Eq. 2.2)}$$

where ΔS is the change in surface storage (amount of ponded water), P is precipitation, I is infiltration, ET is evapotranspiration (which may also include "interception" of rainfall by plants), and R is runoff.

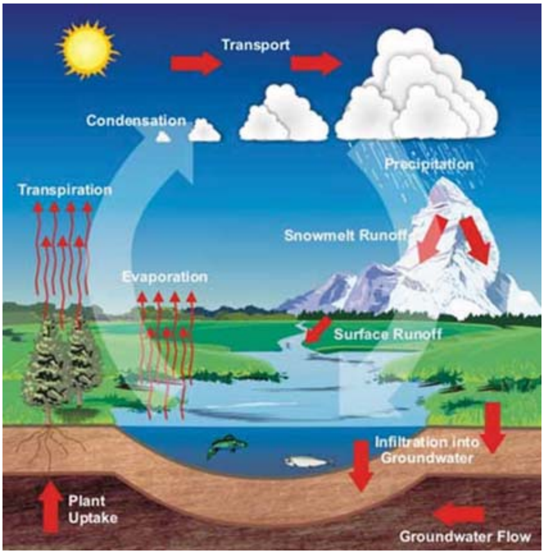

Figure 2.4 Hydrologic processes in a watershed.
Source: US National Weather Service (2005).

While simple in concept, developing an accurate water budget may be difficult in practice due to uncertainties and impracticalities in measuring each of the water budget components. In addition to uncertainties surrounding possible land use changes that affect runoff and infiltration, climate variability and change create critical uncertainties for these water budgets. Changes in precipitation patterns and temperature due to climate variability and change must be considered. Chapters 3 and 4 provide some critical knowledge and techniques to help understand how best to incorporate climate information in such models.

There may also be challenges in measuring the variables in Equation 2.2. While precipitation may be measured at multiple gauges throughout the watershed, precipitation can vary significantly even over short distances. Runoff may be estimated as the increase in streamflow volume over a **base flow**, which is the constant (or nearly constant) flow occurring during dry periods due to **surface-groundwater interactions**. Infiltration and evapotranspiration are difficult to measure directly, however. For even rough estimates of these components of the hydrologic cycle, simplified methods using **tabulated coefficients** (standard values based on soil properties and site location) may be needed. The partitioning of precipitation into the components of infiltration, evapotranspiration, surface storage, and runoff depends on a number of factors. These include land use, land cover, soil type, slope, and climatic variables such as temperature, wind, and humidity. Accepted methods that incorporate these parameters in watershed models are discussed in a number of engineering hydrology textbooks (e.g. Wurbs & James, 2002; Bedient *et al.* 2008).

Models that incorporate physically-based parameters may be able to simulate the effects of climate changes on a particular location. Physically-based parameter estimates (e.g. infiltration rates based on observations of soil type) also provide a way of making predictions in basins where no streamflow data is available given the availability of data related to the physical characteristics of the basin. However, it should be expected that predictions in ungauged basins will have much more uncertainty than predictions in gauged basins.

Statistical modeling

While the models discussed above utilize physical parameters, some models are based on empirical data and statistical relationships between chosen parameters and streamflow. These **statistical models** can be helpful when the physical characteristics of the watershed are poorly understood or difficult to measure and model. They may also offer predictions with longer time horizons, particularly if patterns in climate variability can be modeled. For example, seasonal streamflow may be predicted using a statistical model based on ocean-atmosphere variables such as sea surface temperature (SST). An example would be a **linear regression model** between average seasonal SST at a certain location and streamflow at the location of interest (this will be discussed in more detail in Chapters 3 and 4).

Statistical models of streamflow are also often used to generate large samples of plausible streamflow data using the statistics of the historical streamflow data. This can be useful to test the sensitivity of a water resource system to a larger set of conditions than the historical record offers. A wide variety of approaches are available. An introduction is provided in Salas (1993).

Data use

Regardless of whether the model is physically-based, statistical or a combination of the two, historical data can be critical. Ideally, a basin will have adequate precipitation and streamflow data to allow for model calibration and verification. If the model is to be used for flash flood prediction, data for several storm events will be required at short intervals (daily, hourly, or even less). If the model is to be used for seasonal streamflow prediction, continuous flow data will be required at monthly-to-seasonal intervals over a period of 10–20 years or more, since some patterns and trends may only be detectable over multiple decades. While changing conditions, particularly in climate and land use, can impact streamflow and precipitation patterns to the degree that they change significantly from the historical record, it is critical to have as much information as possible about past conditions to provide a baseline and foundation for understanding possible patterns and relationships (Table 2.1).

Table 2.1 Watershed models.

Watershed Model	Reference
HEC Hydrologic Modeling System (HEC-HMS)	USACE (2000)
Soil Water Assessment Tool (SWAT)	Arnold *et al.* (1998)
Precipitation-Runoff Modeling System (PRMS)	Leavesley *et al.* (1983)
‘abcd’ Model	Thomas *et al.* (1983)

Selection of commonly used physically-based watershed models recommended for seasonal stream flow prediction. There are many commercial and public domain watershed models available for seasonal stream flow prediction. Singh and Woolhiser (2002) provide a comprehensive review of watershed models and modeling techniques.

Section 1.2: Predicting water availability for regulated flows in reservoirs

Streamflow variability, particularly extreme high flows and dry periods, can have significant consequences for those relying on or affected by flows in a watershed. Storage reservoirs can be used to reduce the variability of streamflows by storing high flows for release during drier periods. Comparing Figures 2.5 and 2.6 to the time series and flow-duration graphs of Figures 2.1 and 2.2 reveals the effect of regulated flows on the Chagres River downstream of Madden Dam.

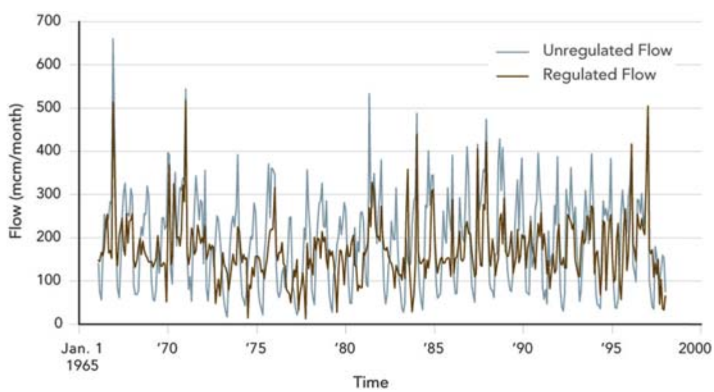

Figure 2.5 Time series of flows on the Chagres River, Panama.
Natural (unregulated) flows are shown in blue and regulated flows are shown in brown. Regulated flow is generally less variable. Units of flow are million cubic meters (mcm) per month. *Data source:* USACE (2000).

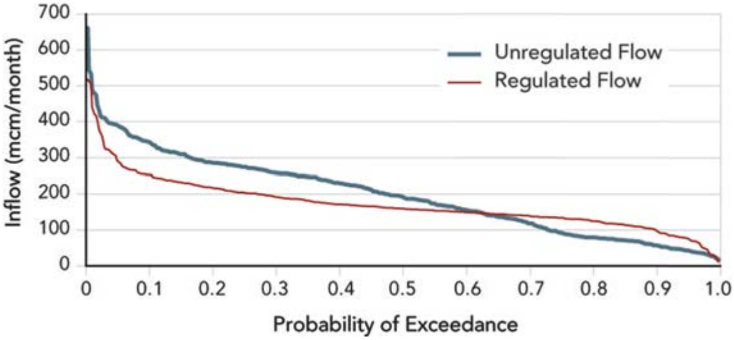

Figure 2.6 Flow-duration curves for flows on the Chagres River, Panama from 1966–1997.
Unregulated flows are shown in blue and regulated flows are shown in red. Regulated flows less frequently exceed very high levels or drop below very low levels. Units of flow are million cubic meters (mcm) per month. *Data source:* USACE (2000).

Figure 2.5 demonstrates the reduced variability, as shown by the reduced peak flows and increased low flows for the dammed river for each period. The **flow-duration curves** shown in Figure 2.6 capture the ability of the storage reservoir to both increase the flow during dry periods (flows less frequently drop below very low values) and reduce particularly high flows. These advantages of storage reservoirs are critical for managing climate variability and may gain in importance as the climate becomes more variable or experiences long-term changes. As Section 1.1 demonstrated, flow-duration curves can also be used to understand the effects of shorter-term climate variability and cycles (such as ENSO), which can offer critical information for understanding the possible role of a storage reservoir for a given system. Exercise 1 allows you to explore these concepts by creating a flow-duration curve and historical data to understand how ENSO conditions can affect inflow for a reservoir.

Exercise 1: Sizing a reservoir and constructing yield-reliability curves using climate information

Exercise 1 provides the information and skills necessary to develop a reservoir yield-reliability curve and understand how it is affected by changes in water demand or inflow. After examining how inflows and demand affect storage requirements for a reservoir, you will create a curve that tracks the reliability based on changing yields for a reservoir with a given capacity. The exercise also allows you to explore the impact of climate conditions on inflow and reliability. This promotes an understanding of how seasonal climate information can be used to determine the necessary size of a reservoir and the expected reservoir reliability.

Again, while the time series and flow-duration graphs provide information about the past, prediction of regulated flows requires additional analysis. Predicting regulated flows involves a two-step process: (1) prediction of unregulated inflow to the reservoir, and (2) detailed **simulation** of reservoir performance and other hydrologic variables such as seepage and evaporation. The section below explores this second step of the process.

Modeling of storage reservoirs

A similar **water budget** equation as used for watersheds can be applied to model storage reservoirs:

$$\Delta S = Q^{\mathrm{in}} + P - E - Q^{\mathrm{out}} - G \qquad \text{(Eq. 2.3)}$$

where ΔS is the change in storage, Q^{in} is inflow, P is precipitation (onto the reservoir surface), E is evaporation from the reservoir surface, and Q^{out} is the total outflow, or release. The total outflow is often divided into components such as releases for hydropower, releases for flood control, and uncontrolled releases (spills). In some cases, seepage to groundwater or through the dam, G, may also be important.

As with the components of the watershed water balance in Equation 2, several of the components in Equation 3 are affected by climate variability and change. Precipitation, inflow and evaporation might all be impacted to some degree by changes in the climate at different time scales. This influence motivates the need for a better understanding of the climate system and its predictability, and also provides the foundation for understanding how climate information can be used in reservoir operations and management.

To accurately model releases from different outlets (e.g. conduits, gates, spillway), evaporation (a function of surface area), and hydroelectric power generation (a function of reservoir elevation and discharge), some basic physical relationships for the reservoir are required. These include reservoir surface elevation vs. area, elevation vs. volume, and elevation vs. discharge capacity curves, as shown in Figure 2.7.

It is important to integrate these physical relationships with knowledge of land use changes, climate variability and longer-term trends in the climate. The interaction between these factors will affect modeling results for different watersheds and reservoirs, if appropriately considered. Land use change, climate variability and long-term changes in climate may affect different reservoir systems at varying degrees based on their physical characteristics. For example, a reservoir with large water surface area to watershed area ratio is likely to have levels significantly affected by changes in the precipitation-evaporation balance. However, other reservoirs may be more affected by changes in watershed runoff. For example, deforestation within a watershed may lead to significant sedimentation in the reservoir, affecting the storage volume. The climate and prediction information addressed in subsequent chapters can also be combined with the risk management techniques discussed in later chapters to understand how best to approach these possible impacts and their uncertainties.

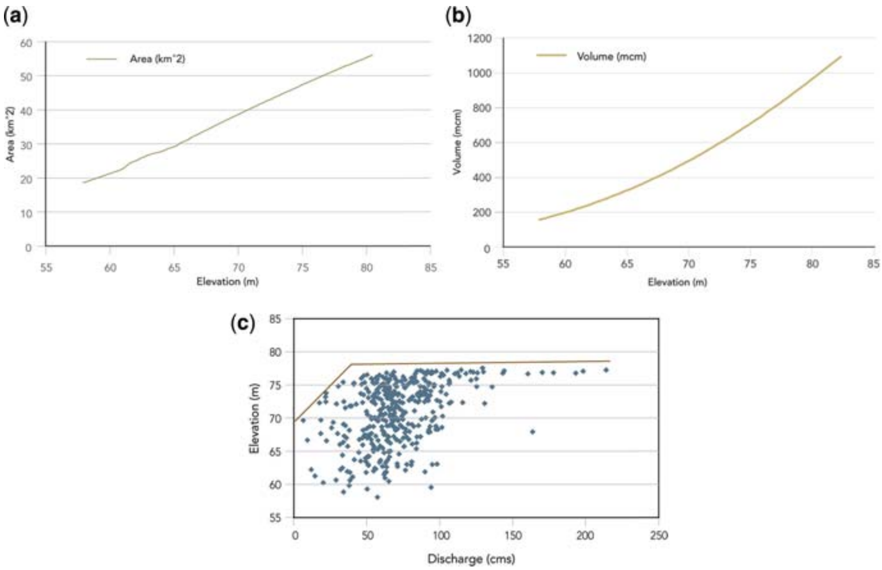

Figure 2.7 Reservoir relationships for Lake Alajuela in Panama.
Panel (a) shows the elevation-area relationship, (b) shows the elevation-volume relationship, and (c) shows the elevation-discharge relationship. The brown line in Panel (c) reveals the boundary defining the relationship between threshold levels of elevation and discharge. *Data source:* USACE (2000).

Section 2: Managing availability with storage

Given that one of the principal goals of water resources management is to control the availability of water, it is essential to understand how to utilize water availability information and predictions to appropriately plan for its storage and use. This information should be used across time scales for both water management planning and operations purposes. For example, reservoir design requires knowledge of historical streamflow, current water needs and projections for the future of both water input and output. Effective reservoir operations also rely on demand and inflow projections, but on a much shorter time scale.

Section 2.1: Reservoir sizing and design

Once data about streamflow and water availability obtained (through the above methods, for example), a common problem in reservoir design is determining the storage capacity required to provide a given yield (or release) with a high level of reliability. There are a number of methods for calculating the necessary storage capacity. One technique is to iteratively select different trial capacities and perform a simulation using the **storage accounting equation** (Equation 2.3 above).

Alternatively, a graphical approach known as a **Rippl Diagram** (Hall & Dracup, 1970) can also be used, as shown in Figure 2.8. In this approach, assuming a constant yield (release from the reservoir), the cumulative inflow curve is plotted along with the cumulative yield. Tangent lines parallel to the yield curve are then drawn at inflection points on the inflow curve. These inflection points represent times when the inflow rate is the same as the yield (release rate), and thus storage in the reservoir is not changing. Whenever the inflow curve has a greater slope than yield curve, the storage is increasing; and whenever the inflow curve has a slope less than the yield curve, the storage is decreasing. The maximum vertical distance between two successive tangent lines, representing the difference in volume between a full and empty reservoir, gives the storage capacity required to provide the specified yield.

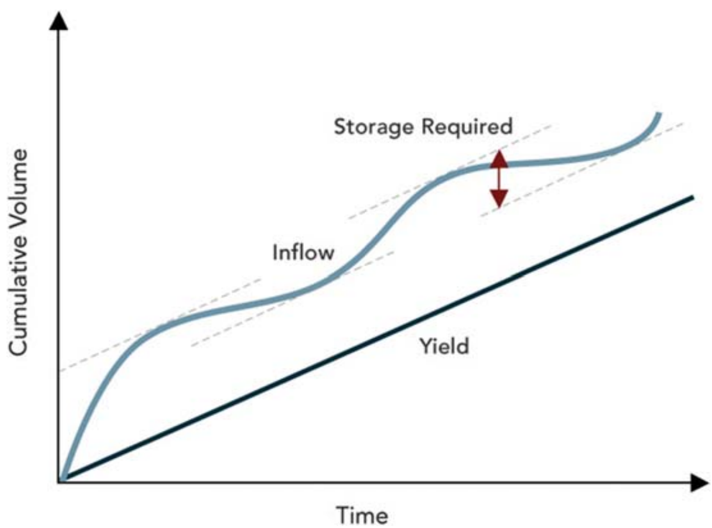

Figure 2.8 Rippl Diagram indicating the storage volume required to meet a given (constant) yield.
The maximum vertical distance between two successive tangent lines represents the difference in volume between a full and empty reservoir and provides the storage capacity required to provide the specified yield. *Source:* Adapted from Hall and Dracup (1970).

Optimization modeling can also be used to determine the minimum storage capacity required to meet a given yield, or to determine the maximum yield for a given capacity, or to evaluate the trade-off between storage capacity and yield.

Below are two related linear programming models for minimizing storage capacity, K, and maximizing yield

$$\begin{aligned}
&\text{Min}\,K \\
&\text{subject to} \\
&S_t = S_{t-1} + Q_t^{\text{in}} - \mathit{Yield} - Q_t^{\text{spill}},\ \forall t \\
&0 \le S_t \le \text{K},\ \forall t \\
&Q_t^{\text{spill}} \ge 0,\ \forall t
\end{aligned} \qquad \text{(Eq. 2.4)}$$

$$\begin{aligned}
&\text{Max}\,\mathit{Yield} \\
&\text{subject to} \\
&S_t = S_{t-1} + Q_t^{\text{in}} - \mathit{Yield} - Q_t^{\text{spill}},\ \forall t \\
&0 \le S_t \le \text{K},\ \forall t \\
&Q_t^{\text{spill}} \ge 0,\ \forall t
\end{aligned} \qquad \text{(Eq. 2.5)}$$

In the first case, capacity K is a variable, and the yield is a constant; in the second case, yield is a variable, and K is a constant. In both models, precipitation, evaporation, and seepage are neglected for simplicity, but these could be included in the water budget constraint. S_t is storage at time t, S_{t-1} is the storage at time $t-1$ (time period before the period being modeled), Q_t^{in} is inflow at time t, *Yield* is the amount released from the reservoir, and Q_t^{spill} is the amount spilled at time t.

These optimization models can only provide approximate solutions due to the simplifications required. In reality, releases from a storage reservoir will be based on a set of (possibly complex) operating rules. Thus, accurate assessment of yield-reliability relationships will require more detailed simulation modeling. There is the opportunity to work with a simplified optimization model in Exercise 1.

Importantly, assumptions of stationarity underlie all three of these methods. Visualization of the storage required in the Rippl Diagram relies solely on the historical record of inflow. Similarly, the optimization technique both removes certain components for simplicity and utilizes a historically-based inflow parameter. As discussed in Section 1, the assumptions of stationarity and the reliance on historical inflows can undermine the results in these models. If the historical record does not sufficiently capture climate variability, or the system faces possible impacts from climate change, these reservoir sizing techniques might lead to inefficient (if storage needs are overestimated) or inadequate (if needs are underestimated) reservoir design.

Section 2.2: Reservoir operations

Once a reservoir has been developed, the next level of management is the actual operation of the reservoir. Operations typically follow some form of operating rule. For example, a **standard operating policy (SOP)**, as shown with the solid line in Figure 2.9, simply releases either the target amount or all the water available in each time period. If the reservoir is at capacity, the excess must also be released (spilled).

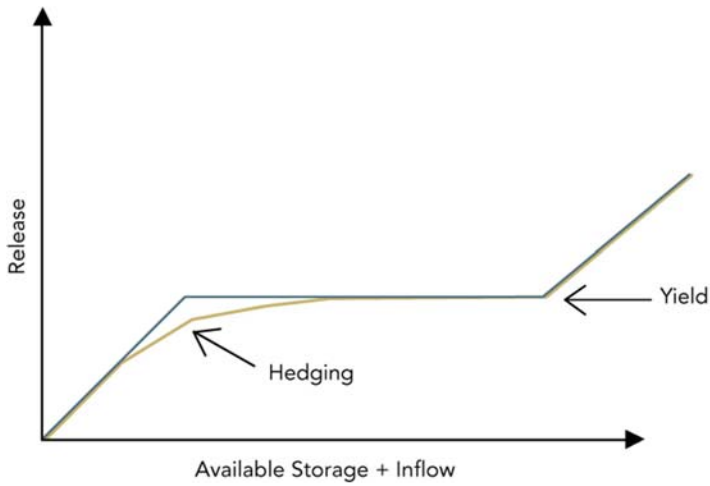

Figure 2.9 Standard operating policy and hedging policy.
A standard operating (dark blue line) and a hedging policy (light brown line) show that at low levels of inflow and available storage, all available water is released, but without meeting the target demand. Whenever a sufficient amount of water is available to meet the target, the target amount is released (horizontal segment). At some level, the water in the reservoir is too high and excess is released or spilled (line with positive slope to the right of the horizontal segment). Following the hedging policy results in less water being released at lower available volumes (i.e. for low inflows, an amount less than the target is released even if there is sufficient water available to meet that demand). This increases the overall frequency of shortfalls, but reduces frequency of extreme shortfalls. *Source:* Adapted from Wurbs (1966).

To demonstrate the use and results of applying such an operating policy, one can assume that the reservoir inflows are those shown in Figure 2.1, and that there is a storage capacity of 1234 mcm. The amount of water demanded from the reservoir (or yield) is varied from 170 to 235 mcm/month to develop a trade-off curve between the yield and reliability. Reliability is calculated simply as the fraction of months during which the supply target is met. The results are shown in Figure 2.10.

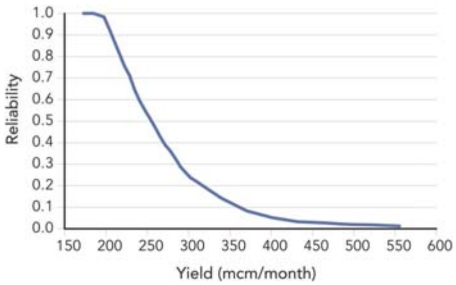

Figure 2.10 Yield-reliability relationship based on the standard operating policy (SOP).
Reliability represents the fraction of months during which the supply target is met. A value of .8 means it was met 80% of the time. *Data source:* USACE (2000).

The SOP is the policy that maximizes **reliability** as computed in this simple way. However, this can actually lead to severe shortfalls of significant magnitude when they do occur. A **hedging policy**, as shown with the brown line in Figure 2.9, can be followed to reduce the magnitude of the shortfalls. A hedging policy accepts a greater number of small shortfalls in return for fewer severe shortfalls. The expected severity of a shortfall, given that a shortfall occurs, has been termed the **vulnerability** of a system. A related metric is **resiliency**, which measures how quickly the system recovers following a shortfall (Hashimoto *et al.* 1982). Table 2.2 compares these metrics for the SOP and hedging policy.

Table 2.2 Performance metrics for standard operating policy (SOP) and a hedging policy.

Policy	Vulnerability	Resiliency	Reliability
SOP	45.1	0.124	0.757
Hedging	40.4	0.273	0.683

Lower values for Vulnerability and higher values for Resiliency and Reliability are desirable. The hedging policy offers improved resilience and reduced vulnerability at the expense of decreased reliability. Data source: *USACE (2000).*

Both the SOP and the hedging policy are developed based on historical flow data and typically assume stationarity when applied. While it may sometimes be appropriate to select inflow values from the historical record to represent possible future conditions, it is often advantageous to use inflow forecasts based on antecedent conditions or climate information. Figure 2.11 reveals the significant impact ENSO conditions can have on the yield-reliability results for a given season due to changes in the precipitation and resulting streamflow.

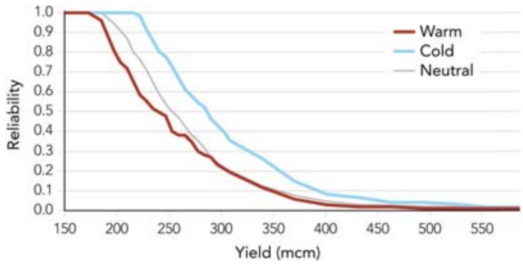

Figure 2.11 Yield-reliability curve conditioned on the Equatorial Pacific SST in July–September.

The NINO3.4 index is used to define the Equatorial Pacific state as follows: $>0.5C =$ Warm (El Niño); $<-0.5C =$ Cold (La Niña); between $-0.5C$ and $0.5C =$ Neutral. Increased flows following the cold periods result in increased reliability across all yields. *Source:* Chagres River data, USACE (2000); SST data from NOAA NCDC ERSST v.2.

One method for addressing the nonstationarity is to use position analysis (Hirsch, 1978), a simulation procedure that can forecast risks associated with a specific operating policy over a number of months or seasons, conditioned on the current reservoir storage level. Figure 2.12 shows an example based on 12-month traces sampled from the historical flow record.

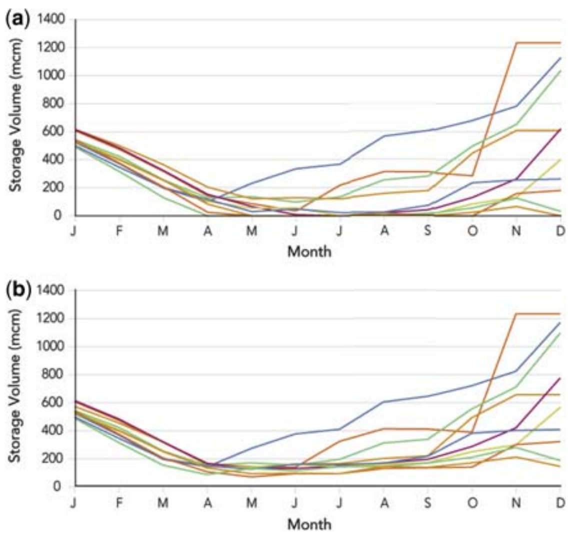

Figure 2.12 Position analysis based on historical inflow traces.

Panel (a) shows traces using the standard operating policy (SOP), and Panel (b) shows traces using the hedging policy. Each trace represents the storage volume based on the given operating policy and inflow from a specific year in the historical record. The hedging policy prevents the storage volume from dropping below a threshold level of around 100 mcm. *Data source:* USACE (2000).

In practice, these flow traces could be selected (or generated) in a way that incorporates climate forecasts (discussed more in Chapters 3 and 4).

CONCLUDING REMARKS

This chapter has provided some basic background on ways in which climate information, both forecasts and historical records, can be used and integrated into the management of water availability. We demonstrate the importance of climate variability on inflows, with selected illustrations based on the ENSO phenomenon at the seasonal time scale. The next chapter provides additional information on climate variability across various time scales, and Chapter 4 introduces basic methods of forecasting such climate variability and change. It is critical to remember that while the tools offered above and later in this manual can support the understanding, modeling and prediction of hydrologic and climatic variables, there remain significant uncertainties in the information and forecasts. Thus, the analysis must be combined with an appropriate approach to managing the resulting risks and possible opportunities (as described in Chapter 5).

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Chapter 3

Climate variability and hydrologic predictability

INTRODUCTION

Advances in the understanding of climate variability have led to enhanced capabilities for the provision of hydrologic information, including improved seasonal streamflow forecasts. These capabilities offer significant opportunities for improved water resources management in many parts of the world. This chapter provides a general overview of some key aspects of the climate system and their relationship to hydrologic predictability. We highlight climate concepts most relevant for hydrological predictability, including an overview of different time scales of climate variability; the physical basis for seasonal climate forecasts; El Niño-Southern Oscillation (ENSO) and the global extent of its effects on seasonal climate ("teleconnections")[1]; and climate variability over longer time scales and its relevance to water resources management.

Section 1: Time scales of climate variability

The physical attributes of the climate system (e.g. the dynamics and thermodynamics of the atmosphere and ocean, rate of rotation of the earth, etc.) determine the times scales of its variability. One key distinction is the difference between climate and weather. *Weather* describes conditions on time scales of a few days or less, while *climate* refers to aggregates of weather conditions on time scales of a month or more, and their longer term modulation. Typically, the larger the spatial scale of a climate phenomenon, the longer its characteristic time scale. As a hydrologic example, the flow rate of the Amazon River, the world's largest

[1]For information on ENSO and current climate conditions, visit http://iri.columbia.edu/climate/ENSO/. You can also view a free online course regarding the ENSO phenomenon at http://www.meted.ucar.edu/climate/enso/, hosted by the Cooperative Program for Operational Meteorology, Education and Training (COMET Program) of the US National Weather Service and the University Corporation for Atmospheric Research.

river, would be expected to vary much more slowly than streamflow in a very small watershed.

The climate is rich in its diversity of physical phenomena, which operate on a continuum of time scales ranging from seconds to millennia. Figure 1.1 illustrates some of the key climate phenomena affecting water resources, along with their associated spatial and temporal scales.

The various time scales of variability overlap and operate simultaneously on a given system. For example, some form of decadal variability might be affecting the strength of an interannual pattern, which itself is affecting the aggregate weather conditions within a season. Conversely, the accumulated result of random weather fluctuations over time also causes decadal variability in climate records. Figure 3.1 demonstrates three key timescales through *detrending* a precipitation time series.

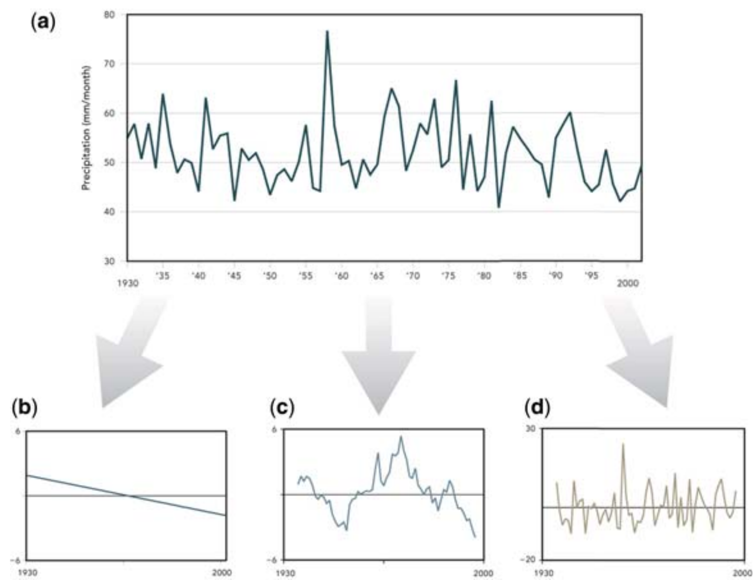

Figure 3.1 Time-scale elements of a precipitation time series.
The series is separated into three scales that help in thinking about managing climate risk. Panel (a) at the top shows the raw annual time series, while the bottom figures illustrate the contribution of each of the three scales of variability. Panel (b) shows the long-term linear trend; (c) shows the decadal variability based on a running 10-year average; and (d) shows the interannual variabity obtained by subtracting the decadal and trend anomalies from the annual anomaly. The three bottom panels are in units of anomaly (mm/month) from the long-term mean, and the solid horizontal line represents the long-term mean (anomaly value of 0). Note the much larger scale for the interannual variability shown in Panel (d), illustrating that variability at the interannual time scale is the dominant element in this time series. *Source:* Annual precipitation data from Centro de Ciencias de la Atmósfera (CCA) at the Universidad Nacional Autónoma de México (UNAM).

Section 2: Time scales and forecasts

The time scales of different aspects of climate variability play a key role for hydrologic forecasting. For example, weather forecasts, such as what the maximum temperature or amount of precipitation is likely to be over the next few days, are only skillful up to approximately five to ten days into the future due to the inherent "chaotic" nature of atmospheric variability. These short-term weather forecasts are sometimes called "deterministic" forecasts because they attempt to predict the specific value of a given variable. Water resources managers typically utilize such forecasts for flood prediction and control.

Longer term climate forecasts can also be useful for water resources management, providing expected precipitation estimates over a season, for example. The climate and weather forecasts are different in a critical way. Since individual weather systems cannot be predicted at these longer time scales, seasonal and longer-term climate forecasts can only indicate a change in the *odds* of conditions being higher or lower than some level. For example, a seasonal precipitation forecast can indicate a change in the probability that the season will be wetter or drier than some reference amount, such as the 30-year average precipitation for the season and location considered. As such, seasonal forecasts are necessarily ***probabilistic***.

A probabilistic climate forecast differs significantly from a deterministic weather forecast. While a deterministic weather forecast might predict 20 mm of precipitation for the coming week, for example, a probabilistic seasonal climate forecast could indicate that there is a 50% probability this season's precipitation at a particular location will be among the 10 wettest observed over the past 30 years. Figure 3.2 illustrates the differences between deterministic and probabilistic forecasts and the information they communicate. Seasonal forecasts can be tailored[2] to be more relevant to water management needs by predicting a hydrologic variable (e.g. inflow to a reservoir) rather than precipitation, but they will still remain probabilistic. More sophisticated weather forecasts are also presented probabilistically, recognizing the inherent limitations of deterministic weather prediction.

Physical basis for seasonal predictions

Advances in climate science have provided the ability to generate skillful seasonal climate or climate-based hydrologic forecasts. The physical basis of seasonal forecasting derives largely from 1) the long "memory" of the upper ocean, whose thermal capacities and motions are much larger/slower than those of the atmosphere, together with 2) the sensitivity of the tropical atmosphere to

[2]Tailoring a forecast is the development of techniques to make seasonal forecasts more applicable and skillful for a certain sector, such as water resources.

underlying sea surface temperatures (SSTs). The underlying concepts are simple: the atmosphere is heated most where the underlying ocean is the warmest, warm air tends to rise, and rising motion generates clouds and precipitation (Figure 3.3). This process on seasonal timescales is a key one in the tropics.

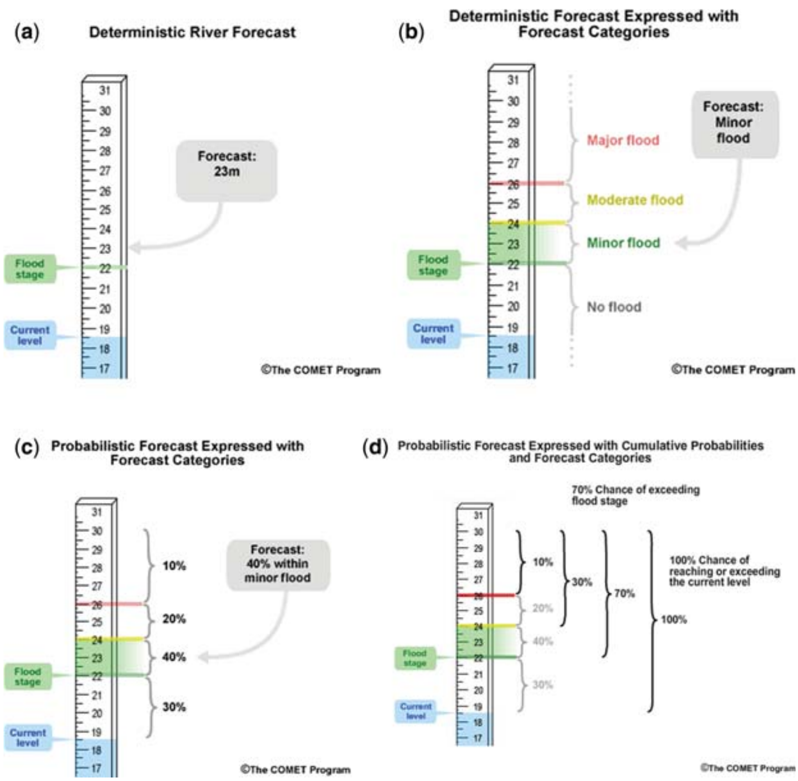

Figure 3.2 Distinguishing between a deterministic and probabilistic forecast. Panel (a) shows an example of a deterministic forecast that predicts a specific inflow level; (b) shows a deterministic forecast that predicts a specific inflow category; (c) shows a probabilistic forecasts that predicts the probability of inflow falling into each category; and (d) shows a probabilistic forecast that predicts the probability of inflow for each category as well as cumulative probabilities across categories of increasing inflow. *Source*: COMET® Website.

The impact of SSTs on precipitation and wind patterns in their local vicinity influences wind patterns, rain and temperature in regions farther away. In this way, a very large area of warm tropical SSTs and precipitation can impact wind patterns and rainfall over a large area of the globe. These remote influences are sometimes called "teleconnections" meaning "influence at a distance".

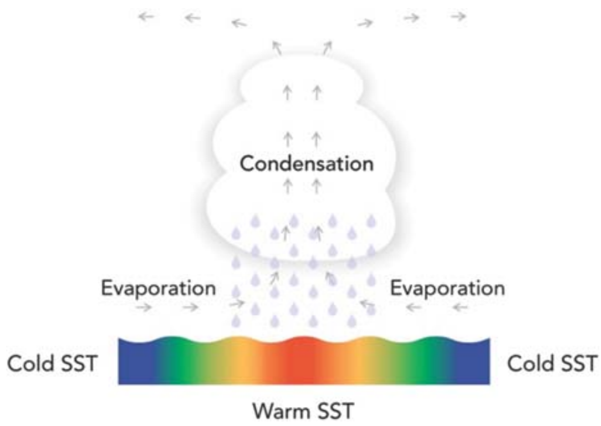

Figure 3.3 A key mechanism for tropical climate on seasonal timescales. Precipitation and low pressure tend to occur over tropical ocean areas with the highest SSTs (shown here with redder colors). Winds converge over the area of low pressure and result in rising motion. The rising warm moist air cools, leading to condensation into clouds and rainfall.

As tropical SSTs tend to change relatively slowly (important patterns of tropical SSTs often persist for several months or more), this provides the physical basis for making climate predictions. The most important phenomenon that affects large-scale patterns of SST, precipitation and winds over much of the tropics and (through teleconnection mechanisms) into regions outside the tropics is the El Niño-Southern Oscillation (ENSO) phenomenon.

Section 3: ENSO and its teleconnections

Under average (or "normal") conditions, winds known as "trade winds" blow toward the equator from east to west across the tropical Pacific Ocean, from over the relatively cool waters in the east towards the warmer waters in the west. Upward motion of the air and heavy rainfall occurs over the western tropical Pacific where SSTs are comparatively high (Figure 3.4). At higher levels in the atmosphere, the air tends to flow in the opposite direction of the surface winds and descend over the cooler waters in the eastern tropical Pacific, tending to "close the loop" (see Figure 3.4).

The ENSO phenomenon involves the irregular warming or cooling of the tropical Pacific Ocean (relative to its average state) and the resulting changes in large-scale patterns of precipitation and wind. During an El Niño event (also known as an ENSO "warm event"), the trade winds weaken and the warm surface waters of the western Pacific spread eastward over the cooler waters beneath. This affects the equatorial thermocline, which is the sharp vertical temperature gradient of warmer water sitting atop the cooler water below that tilts upward to the east: the warm surface waters spread eastward and push down the thermocline in the east. The atmosphere responds to the changed SST pattern, leading to an increase in rainfall in the central Pacific and a decrease in the west, further weakening the trade winds and allowing SSTs to warm further. This air-sea coupling results in a positive feedback loop that allows the anomalous pattern to grow and persist for up to six months or more, before ocean dynamics cause the chain of events to reverse. This leads to the ENSO cycle. The ensuing La Niña conditions (also known as an ENSO "cold event") essentially represent an enhancement of the average conditions, with increased easterly trade winds, reduced SSTs in the east-central Pacific, and enhanced rainfall in the western Pacific. The reduced SSTs during a La Niña event tend to decrease rainfall relative to its average value in the east-central Pacific. The general characteristics of different ENSO phases are shown in Figure 3.4, although the ENSO cycle is actually far from regular.

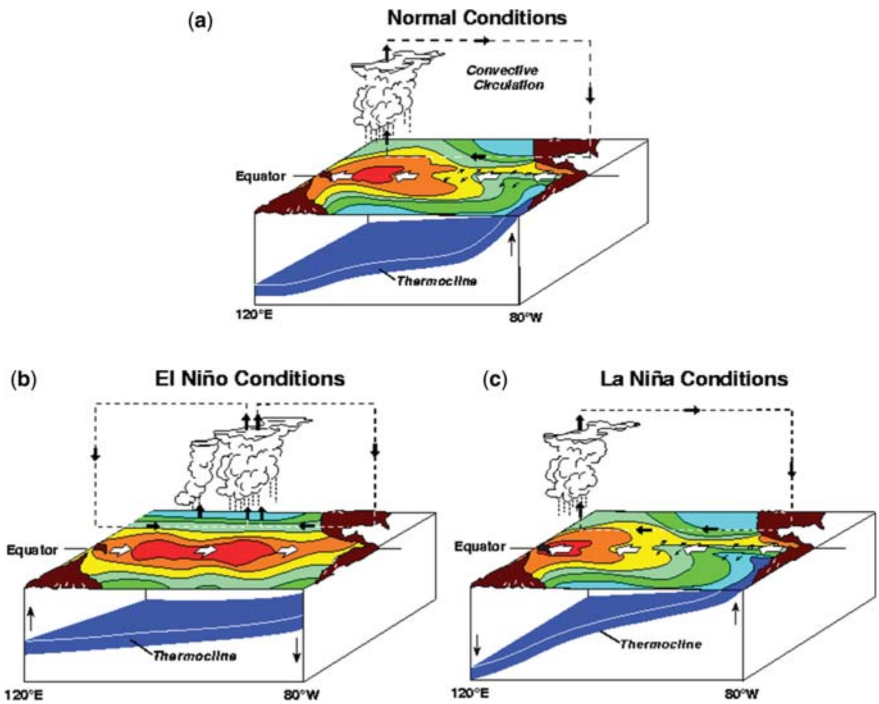

Figure 3.4 Ocean, wind and precipitation conditions in the tropical Pacific during (a) normal conditions, (b) El Niño conditions, and (c) La Niña conditions.
Red colors indicate warmer SSTs, while blue and green indicate cooler SSTs. The images reveal the westward movement of warm waters and precipitation during the El Niño phase (generally decreasing precipitation in the tropics and increasing precipitation in the subtropical regions).
Source: NOAA Pacific Marine Environment Laboratory.

ENSO is among the most predictable components of the climate system on interannual timescales and plays a significant role in interannual climate variability in many parts of the world[3]. As shown in Figures 3.5 and 3.6, the phase of ENSO can have a significant effect on precipitation and other climate indicators, depending on the location and other climate system impacts[4]. The far-flung remote influences of ENSO can be understood most simply as a consequence of the vast size of the tropical Pacific ocean: as the tropical Pacific heats up during an El Niño event (Figure 3.4b), that heat warms the entire tropical atmosphere. A key mechanism is through this tropical warming that stabilizes the atmosphere, tending to produce drought conditions over many parts of the tropics and anomalously wet conditions in some subtropical regions. Because these teleconnections can significantly impact communities in affected regions, ENSO prediction is highly valuable.

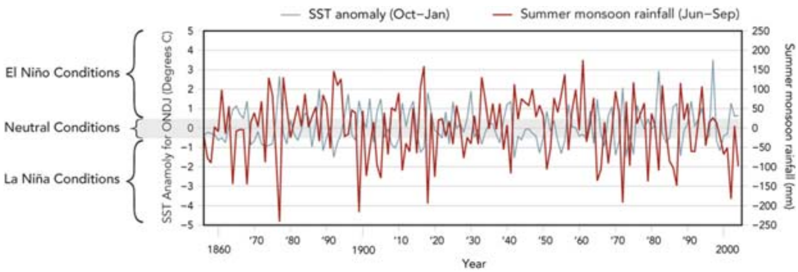

Figure 3.5 Indian summer monsoon precipitation data and ENSO conditions based on SST anomalies for 1856–2004.

Large negative SST anomalies corresponding to La Niña conditions generally result in high precipitation values, while high positive SST anomalies corresponding to El Niño conditions generally result in low precipitation values. A threshold of $\pm 0.5°C$ is often used to determine El Niño/La Niña events. Note: the SST here lags the Indian monsoon. The stronger relationship with ENSO lagging Indian monsoon (as compared to ENSO leading the Indian monsoon) has long been known and investigated. *Source:* Rainfall data, Indian Institute of Tropical Meteorology (IITM); SST data, Kaplan NINO3 index from Optimal Smoother analysis of MOHSST5 monthly SST anomalies. See http://iridl.ldeo.columbia.edu/maproom/ENSO/Climate_Impacts/India_Rainfall.html.

[3]In some situations, ENSO development itself can be predicted, extending the potential lead-time of seasonal climate forecasts (e.g. see Cane & Zebiak, 1986; Philander 1990). The use of coupled ocean-atmosphere models to project forward all aspects of the climate system in a seasonal forecast, including ENSO, is discussed in Chapter 4, Section 2.2.

[4]Other climate system impacts are beyond the scope of this discussion. See additional reading at the end of the chapter. In particular, in many regions it is important to be aware of tropical Atlantic and tropical Indian Ocean impacts (e.g. see Hurrell *et al.* 2006; Kushnir *et al.* 2006; Goddard & Graham, 1999).

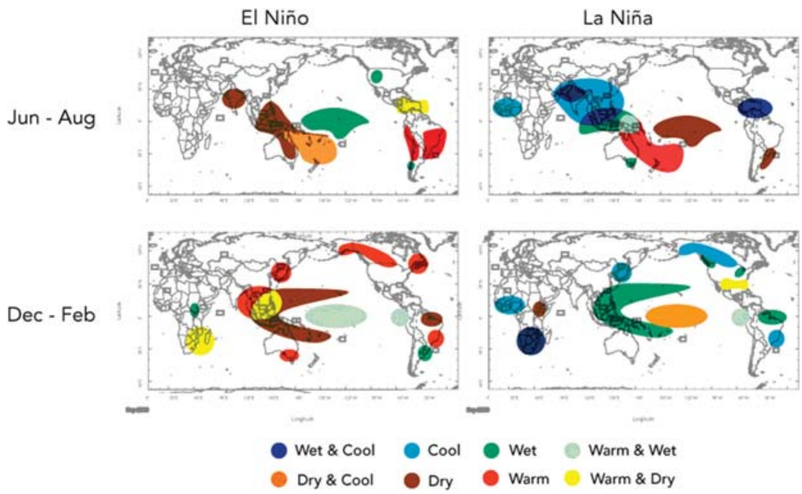

Figure 3.6 Typical ENSO teleconnections associated with seasonal temperature and rainfall changes during El Niño and La Niña events.

These maps show regions that, on average, have particularly clear and persistent climate anomalies during El Niño and La Niña events. They do not represent all ENSO impacts. For any given region, it is recommended to consult a climate system expert of that region to appreciate the nature of typical impacts associated with ENSO and other lesser SST variations, such as in the tropical Atlantic and Indian Oceans. *Source:* NOAA, Climate Prediction Center.

Section 4: Climate variability over longer time scales

While ENSO is the dominant factor influencing interannual variations in rainfall in much of the tropics, other patterns of SST characterize the variability on time scales of a decade or more, with expression in many parts of the global ocean. These phenomena, sometimes known as *lower frequency* variability because the phase changes occur less frequently than interannual variability, have been associated with a number of regional climate variations as well.

The Pacific Decadal Variability (PDV), also known as the Pacific Decadal Oscillation (PDO), is a phenomenon of SST patterns occurring on decadal time scales. The pattern of SST departures from average associated with PDV is shown in Figure 3.7, along with a graph showing its slowly varying evolution.

The SST patterns of PDV resemble those of ENSO, but with more influence from conditions in the midlatitudes that are consistent with the longer time scales of the extratropical oceans. However, physical explanations of PDV are still controversial, and the extent of its predictability has yet to be established. Nonetheless, recognition that there are clearly identified patterns of variability in the climate (and hydroclimate) that persist for multiple years can be of practical use in water management. For example, for river systems that experience such decadal variability, water managers can see that in addition to interannual variability of flows, there may be sequences of several unusually wet or dry years in a row that will obviously have an effect on the water supply (for more exploration of the impact of interactions between ENSO and the PDV on streamflow, see Hidalgo &

EXAMPLE 3.1: Early recognition of the role of decadal climate variability expression in water systems

The Great Salt Lake (GSL) is a closed lake in the arid Western United States that has experienced dramatic historic volume variations in response to hydrological fluxes (Mann *et al.* 1995). After concerns that the GSL was drying up in the 1970s, it rose to its highest level in one hundred years and then quickly receded in the period between 1983 and 1986 (Lall & Mann, 1995). Hydrologists and climatologists began to examine whether the GSL volume variability exhibited any structured pattern, and if this could be connected to large-scale climate patterns. Some researchers initially suggested that variability at the decadal time scale might correspond to sunspot or lunar tide cycles (Labitzke & van Loon, 1988). However, another group of researchers focused on analyzing climatic factors such as precipitation, surface temperature, and sea level pressure to show that changes in climate conditions beyond the local region were connected to fluctuations in streamflow and the Great Salt Lake volume.

The research revealed significant connections between the GSL volume variability and indices measuring atmospheric circulation patterns. They found that atmospheric circulation variations occurring over decadal time scales appeared to drive precipitation variability that affected the GSL volume (Lall & Mann, 1995; Mann *et al.* 1995). At this stage, there was limited understanding of the physical basis for these atmospheric circulations or their drivers. Moon and Lall (1996) came to similar conclusions using a selection of climate indices representing atmospheric circulation patterns (e.g. ENSO and pressure anomalies in the central North Pacific). They revealed apparent atmospheric teleconnections at the interannual (2.5 to 4 years, in this case) and interdecadal (12 to 14 year frequency) time scales.

Importantly, the authors of these papers cautioned that the patterns they identified should be interpreted carefully and without assuming that they represent strict cycles in the climate system. The complex nature of the climate system and the interaction of many different processes across time scales result in variability within identified patterns. Incomplete understanding of the physical basis for these patterns also made it difficult to characterize and predict both the climate patterns and the resulting hydrologic changes in the Great Salt Lake. However, researchers ultimately had the vision that recognizing the role of decadal climate variability in the rise and fall of the GSL could improve the management of impacts from regional anomalous wet periods and droughts (Lall & Mann, 1995).

Dracup, 2003; Dettinger *et al.* 2000). In addition, if the current phase of PDV can be identified, empirical predictions (such as whether it will persist) can be made for the next few years. While factors other than PDV will still affect climate from one season, or year, to the next, this "background" climate state may lead to a shift in the odds for wetter or drier conditions over the coming few years, as an example.

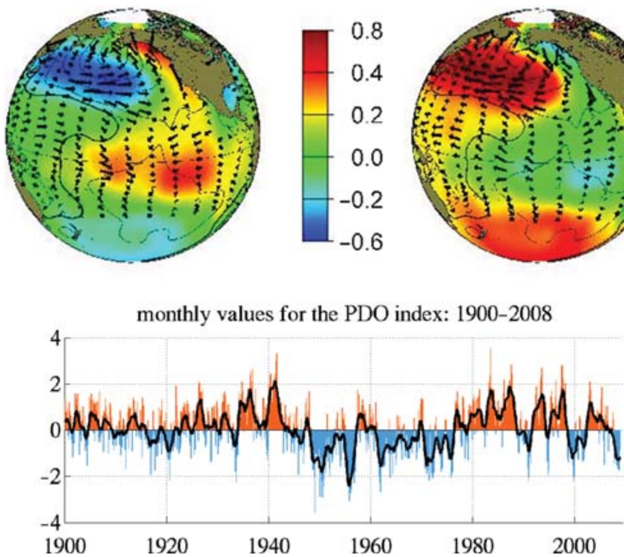

Figure 3.7 SST anomalies and PDV.
Panel (a) illustrates the patterns of SST anomalies associated with the warm (left) and cool (right) phase of the Pacific Decadal Variability. The colors show the distribution of average winter SST anomalies (in degrees Celsius) during each phase. The contour lines represent the sea-level pressure anomaly patterns, while the arrows show anomaly patterns for surface winds. Panel (b) provides the time series showing the slowly varying nature of these patterns. *Source:* Joint Institute for the Study of the Atmosphere and Ocean, University of Washington.

Over the Atlantic basin, there is a somewhat stronger physical basis for the analogous Atlantic Multidecadal Oscillation (AMO) due to a better understanding of the ocean's thermohaline circulation. Again, though, its predictability has yet to be reliably demonstrated. Similar to the PDV, slowly varying fluctuations in SST in the Atlantic have also been associated with low frequency variations in streamflow in several parts of the world, including across parts of North America, South America and Africa**.** The AMO has also been hypothesized to modulate ENSO on decadal time scales.

EXAMPLE 3.2: Attribution of decadal variability in hydroclimatic systems to regional-scale climate processes – the case of the Atlantic Multidecadal Oscillation

Beginning in the mid-1980s, climate scientists started to identify a large-scale pattern of climate variability associated with fluctuations in the SST in the North Atlantic occurring over multiple decades (Folland *et al.* 1986; Schlesinger & Ramanjkutty, 1994; Mann *et al.* 1995). Further research and studies have revealed periods of roughly 40–70 years of North Atlantic SST variability with a range of 0.4°C that has been labeled the Atlantic Multidecadal Oscillation (AMO) or Atlantic multidecadal variability (short summary in Meehl *et al.* 2009; early example of analysis in Enfield *et al.* 2001). Studies suggest that recent warm phases occurred during 1860–1880 and 1940–1960, and with a new warm phase generally recognized as starting in the mid-1990s. Recent cool phases occurred during 1905–1925 and 1970–1990. Although our understanding of the physical basis for the phenomenon is still somewhat limited, scientists have determined that the patterns are most likely driven by ocean-atmosphere interactions.

While the changes in SST might seem small and are localized in regions of the North Atlantic, this phenomenon appears to have near-global impacts, with the most significant effects felt widely across the North Atlantic basin. The AMO impact has been quantified for multidecadal variations ranging from droughts in the Sahel and precipitation patterns in India, to sea ice concentration in the Greenland Sea and sea level pressure over the southern USA and southern Europe (Trenberth *et al.* 2007; Zhang & Delworth, 2006; Mariotto & Dell'Aquila, 2012). The AMO has also been shown to affect multidecadal variability of river flows and reservoir inflows in various areas. For example, several studies have revealed the significant effect of the AMO on inflows in the United States, including a 40% change in inflows to Lake Okeechobee, Florida based on the AMO phase (Enfield *et al.* 2001).

The AMO acts as a regional-scale climate phenomenon that interacts with other climate patterns operating across different time scales. For example, long-term trends in the global climate may have dampened or accentuated depending on the phase of the AMO (e.g. see Ting *et al.* 2009). Additionally, the AMO appears to interact with interannual impacts from ENSO with varying levels of intensity depending on the region. Outflow of the Mississippi River in the United States is strongly correlated with rainfall, which is connected to ENSO phases. However, the degree to which the rainfall in the Mississippi River basin is impacted by ENSO is significantly affected by the AMO phase (Enfield *et al.* 2001). While El Niño events lead to less rainfall during the AMO warm phase, the conditions during the AMO cool phase offset ENSO conditions and mitigate their impact (see Figure 3.8).

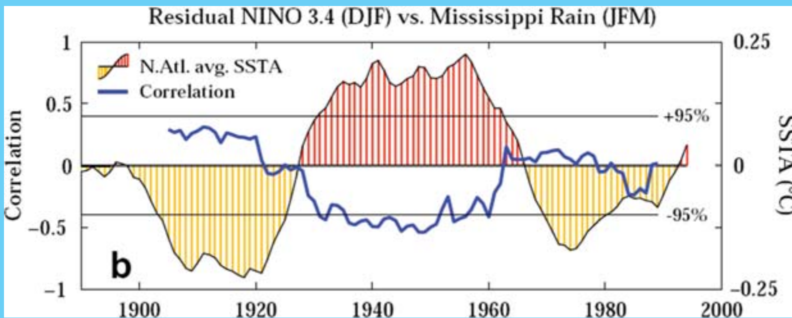

Figure 3.8 AMO and ENSO.
Ten-year running mean of the AMO index (shaded departures) shown in comparison with the 20-year correlation between the NINO3.4 index for Dec-Jan-Feb and the Jan-Feb-Mar rainfall anomaly over the Mississippi basin (blue curve). This demonstrates that the ENSO-rainfall correlation is stronger during AMO warm phases than cool phases. *Source:* Enfield *et al.* (2001).

CONCLUDING REMARKS

Seasonal forecasts of both meteorological and hydrologic variables are now possible because of advances in our understanding of the mechanisms of seasonal-to-interannual climate variability, particularly ENSO. The physical basis for such predictions lies, to a large extent, in the coupling between atmosphere and ocean, and the slower evolution of the latter. Interdecadal variations in SSTs and hydroclimatic variables such as streamflow are also prominent, although the underlying mechanisms are less well understood, and their evolution is still largely unpredictable. However, just recognizing the existence of these low frequency climate fluctuations is nonetheless of practical use to water managers as sequences of unusually wet or dry periods can be expected to occur episodically and can be taken into account when forecasting the range of expected water availability.

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Chapter 4

Climate predictability and forecasts

INTRODUCTION

Chapters 1 and 2 introduced the importance of climate variability and change for water resources management. The tools and models climate scientists develop to forecast climatic variables across various time scales are thus critically important to water resources professionals. It is important for water resources professionals to understand the general procedures for developing these forecasts and quantifying the limitations resulting from uncertainties[1]. Some water management agencies may also be able to use these techniques to develop their own customized forecast products. This chapter summarizes some of the key techniques, models and tools used for prediction of hydroclimatic variables, particularly at the seasonal time scale. It explores a range of forecast models as well as some online software tools to support using climate data information and making seasonal forecasts. The chapter is intended as an introduction to the material, and it is recommended that water resources professionals collaborate with climate professionals to produce the most appropriate and skillful forecasts for their systems.

Section 1: Basic hydrologic forecast models

Traditional approaches to hydrologic forecasting have relied on historical or antecedent observations of hydrologic conditions, typically without consideration of climate predictors. The following section describes some of these models and methods of integrating basic climate information.

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[1]The Cooperative Program for Operational Meteorology, Education and Training (COMET Program) of the US National Weather Service and the University Corporation for Atmospheric Research offer a wide range of helpful teaching modules including climate and hydrology topics. To access these free online courses, visit http://www.meted.ucar.edu/.

Hydrologic persistence

In many locations, observations of antecedent or current watershed conditions can provide useful information for predicting future conditions. The persistence of streamflow (i.e. tendency of high flows to follow high flows, and low flows to follow low flows) is therefore often a useful predictor for lead times of up to 1–3 months or more, depending on the size of river system[2] (as well as the nature of the hydroclimate system). An illustration is provided in Figure 4.1 for the Chagres River in Panama.

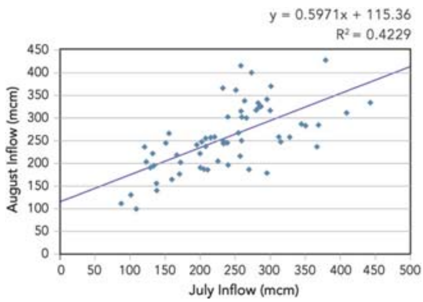

Figure 4.1 Relationship between July and August flows on the Chagres River, Panama.
The linear regression illustrates an example of a simple forecast method. Also note that the area of this watershed is relatively small (approximately 1025 km^2), and thus consistent with highly variable runoff and streamflow. *Data source:* USACE (2000).

The linear regression shown in Figure 4.1 represents a simple statistical model that might be used to predict the monthly flow in August based on the flow observed in July. Since the data do not perfectly follow the regression line, there is uncertainty in this simple forecast of August flow given the observed flows in July. As discussed in Chapter 3, seasonal forecasts are probabilistic and should address and communicate this uncertainty. In this example, the difference between the observed values and the regression line (the error) can be used to estimate the probability for a range of flows or likelihood of exceeding a particular flow.

Ensemble streamflow prediction

Another approach to seasonal streamflow forecasting that utilizes only observations as input is called the Ensemble Streamflow Prediction (ESP) method, originally developed at the United States National Weather Service (Day, 1985). ESP generates probabilistic forecasts by computing multiple streamflow *traces* (or scenarios) using a physically based watershed model. The procedure begins with

[2]Persistence is often stronger for larger river systems because flows typically change much more slowly than in smaller rivers.

a calibrated and verified watershed model, which is updated to represent current watershed conditions (e.g. soil moisture, groundwater levels). A set of historical climate precipitation and temperature time series is then input to the model to generate an ensemble (or set) of streamflow traces. For example, if historical climate data is available for the period 1951–2000 (50 years) and it is desired to make a forecast for the April-May-June period starting from observed conditions in the month of March in a given year, then the 50 individual years of precipitation and temperature data will be input to the watershed model to produce 50 traces, or possible outcomes, of streamflow. Figure 4.2 shows an example of such an ESP forecast.

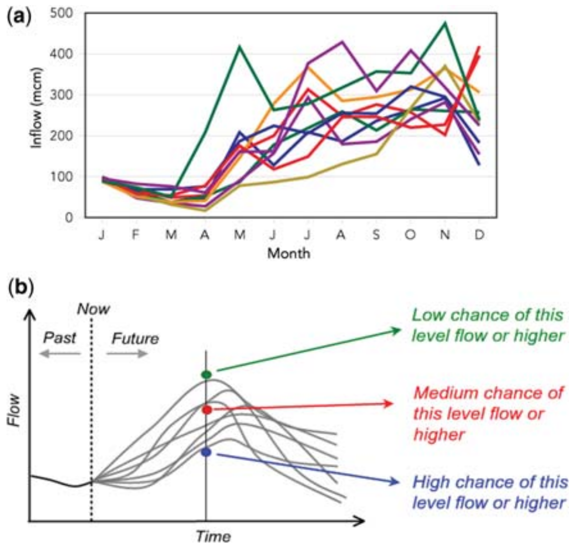

Figure 4.2 Ensemble streamflow and interpretation of a forecast.
Panel (a) shows an Ensemble Streamflow Prediction (ESP) forecast for the Chagres River, Panama. Each line represents a simulated streamflow projection, or trace. Panel (b) provides a guide for how to interpret an ESP forecast. *Source:* Data for (a), USACE (2000); (b) COMET® Website.

In this method each climate scenario is considered equally likely. Thus, each streamflow trace is also considered equally likely. The observed range in climate conditions over 50 years provides a measure of the possible range in streamflows for the season being forecast. However, there is no information included in the model to indicate what past conditions (e.g. unusually wet or dry) are more likely to occur during the forecast period. Thus, while the ESP approach described implicitly accounts for hydrologic persistence and historical variability of climate, it does not explicitly consider forecasted climate information (such as information based on ENSO) nor account for nonstationarity in the system.

Conditional ensemble streamflow prediction

The ESP method can be further modified by considering only those past years that had climate conditions deemed similar to those in progress when the forecast is made. In other words each year of this subset of similar past years represents an *analog* to the current year. A classic example of determining analog years is to consider the state of ENSO, as indicated by an index of SST in the tropical Pacific. The teleconnections described in Chapter 3 suggest that ENSO conditions can affect seasonal rainfall and, thus, streamflow in many regions across the globe. The strength of these associations can often be quantified using historical data[3].

If a streamflow forecast is being made for a region which is known to be affected by ENSO, then one can select analog years from only those past years when an El Niño or La Niña event occurred. This can be used as a simple ensemble of seasonal "forecasts". These climate conditions are then used as inputs to the watershed model. In this method, the resulting streamflows simply represent a sample (i.e. a sub-set) from the full range of streamflows determined when using all past years in the unconditional ESP approach. A danger in the use of analog years is that there may be only a very few cases (e.g. less than 10) that can be considered reasonably good analogs, making the resulting streamflow forecasts very sensitive to sampling error. Nonetheless, the analog method represents a simple *conditional* ESP approach to seasonal streamflow forecasting. An example of such a forecast is shown below in Figure 4.3 for the Chagres River.

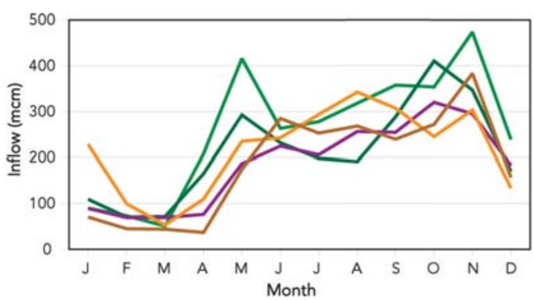

Figure 4.3 Example of combining the ESP and analog approaches to make forecasts for the Chagres River flow during El Niño events.
Each line represents an analog streamflow projection, or trace, based on similar ENSO conditions (e.g. all El Niño events). *Source:* Chagres River data, USACE (2000); ENSO data accessed from NOAA Climate Prediction Center at http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ ensoyears.shtml.

[3]The International Research Institute for Climate and Society provides several resources for exploring ENSO-related impacts. See http://iri.columbia.edu/climate/ENSO/globalimpact/temp_precip/.

Section 2: Further climate-based approaches to seasonal hydroclimatic forecasting

In addition to the simple hydrologic forecast methods described above, water resources managers can make use of hydroclimatic forecasts based on statistical (empirical) climate-based models, dynamical atmosphere-ocean general circulation models (GCMs), regional dynamical climate models (RCMs), or hybrid approaches involving two or more of these types of models. Since dynamical models are very resource-intensive, we focus primarily on the development of relatively simple statistical forecast models that have often been shown to have skill levels competitive with those of dynamical models. The approaches can also be integrated to improve skill. For example, statistical models can create forecasts using either (i) antecedent observed conditions to form statistical predictors of streamflow or, (ii) the output from GCM forecasts to form statistical predictors of streamflow (this latter approach is often referred to as model output statistics, or MOS).

This section begins with an overview of procedures for identifying skillful hydroclimatic predictors and developing statistical forecast models based on predictors identified either from slowly-evolving observed climate variables (primarily SST) or from forecasts made with dynamical models. We then describe the importance of validating forecast models and illustrate validation procedures. We also include a brief discussion of dynamical models and their use in forecasts at seasonal and longer time scales.

Section 2.1: Statistical methods

Statistical climate-based hydroclimatic forecasts require three essential steps. The first critical step is to identify appropriate climate predictors that are sufficiently skillful[4] and have a physical basis. It is then necessary to choose a modeling technique and develop the statistical forecast. Finally, the model and its skill should be validated and evaluated. The following sub-sections explore the key elements of these steps.

Identifying climate predictors

Purely statistical hydroclimatic forecast models have been developed using many different oceanic, atmospheric, and hydrologic predictor variables, including SST, snowpack, and soil moisture. Because of the dangers of overfitting[5] that arise when conducting a random search for predictors, it is advisable to select potential

[4]In general, skill is a measure of a model's ability to predict unexpected or unusual conditions. A well-calibrated model with no skill would create forecasts that are effectively the same as using climatology.

[5]Overfitting is a problem in statistical modeling that occurs when the model describes random error or noise rather than the underlying *(repeatable and truly predictive)* relationships in the data.

predictor variables based on previous recognized prediction studies and in accordance with the current best practices of national or international meteorological/climate prediction centers. If such studies are not available for your specific area, consultation and collaboration with experts in the climate system of the region is encouraged to identify predictors.

There are a large number of statistical methods used to identify and test potentially skillful predictor variables at different lead times.

Linear regression – One of the most basic approaches is to create a simple univariate linear regression between the chosen predictor and predictand (predicted variable). Some sort of screening process can also be used to identify additional possible predictors in a multiple regression, although step-wise regression is not recommended due to the dangers of selection bias (a form of overfitting), especially when the entire dataset is used to select from a pool of predictors. A good practice is to run the linear regression with the chosen predictors on two completely separate subsets of years. If the correlations are not similarly high in both periods, the predictor is not robust.

Partition and compare – The historical record can be partitioned into two or more discrete sets based on a proposed predictor variable. For example, instead of using all years, an ENSO index can be used to classify years as El Niño, La Niña, or neutral. Statistical comparisons can then be run to determine whether the streamflows in the sets are statistically significantly different.

Nonlinear regression or locally weighted regression – Methods such as fitting a polynomial function may be applied if the relationship between the predictor variable and predictand is not expected to be linear.

Principal component analysis – When multiple predictors are to be used in a statistical forecast model simultaneously, they should be tested to ensure that they are not substantially cross-correlated. When predictors are correlated with each other, this introduces problems of multicolinearity when computing the predictor coefficients. This makes the coefficients much less reliable and the model much less likely to be effective when applied in real-time. One solution is to use principal component analysis, since the correlations between the principal component time series are necessarily zero. Principal components regression is also recommended when the number of predictors is large (e.g. when using fields of SSTs) so as to compress the data and avoid problems of overfitting as well as multicolinearity.

Data mining – A broad class of methods widely known as “data mining” do not rely on the assumption of linearity. Instead, they identify synergistic, or strengthening, effects of two or more predictor variables (see Hand *et al.* 2001).

As a final word of caution, predictor variables should not be selected based on statistical correlations alone. It is critically important to identify plausible climate mechanisms (i.e. a theoretical and statistical basis for predictors) that can explain the relationship between the predictor variable and the predictand (predicted variable), and thus provide a physical basis for the forecasts. The primary reason for this is that screening large numbers of potential predictor variables can easily identify inauthentic correlations that (i.e. correlations arising from the chance matching of numbers over the period of correlation calculation), will not lead to robust forecasts.

Understanding the physical basis for the forecast can also aid the forecaster in years when unusual conditions occur, and prevent potential over-reliance on the statistical forecast model. For example, an El Niño event may appear to be strengthening in July and August, but then weaken suddenly in September. Understanding the possible implication of this change in the system, the forecaster may wisely choose to put less weight on the three-month (July–August–September or JAS) ENSO index in developing a forecast of October–November–December (OND) streamflows.

Example 4.1: Simple linear regression

Since ENSO has strong teleconnections in many parts of the world, a predictor variable (or field) that captures ENSO conditions is very often useful. As an example, seasonal rainfall in the Philippines is known to be affected by ENSO, with ENSO warm events frequently contributing to dry conditions in many areas (and cold events leading to wet conditions). It is important to study the relationship at different times of the year, as the impact of ENSO may vary through the year. In this case, researchers have found that the relationship between seasonal rainfall and ENSO reverses sign during boreal summer (or JAS), relative to the general relationship mentioned above (Lyon *et al.* 2006). This indicates that an ENSO index, such as the NINO3.4 SST index (defined by the spatial average of SSTs over the region [5S–5N; 170W–120W]), would likely be a good predictor for streamflow in the Philippines, but models need to note the sensitivity of time of year for the nature of the relationship. Note that this is a method that can be used for predicting inflow directly based on ENSO conditions if a long historical record of streamflows is available for constructing the regression model. Thus, there is no need to forecast precipitation first and to then apply a streamflow model.

As an example, we develop a simple linear regression model relating OND 3-month total inflow at the Angat Reservoir to the preceding JAS NINO3.4 SST index, using the period 1968–2007. The results, shown in Figure 4.4, reveal a significant correlation, which indicates a level of association potentially useful to water managers and motivates further forecast model testing (see Chapter 4, Section 2, evaluation of forecast model skill). Generally speaking, the forecast skill of any model will vary with the lead time of the forecast, with short lead times typically having greater skill than longer lead times.

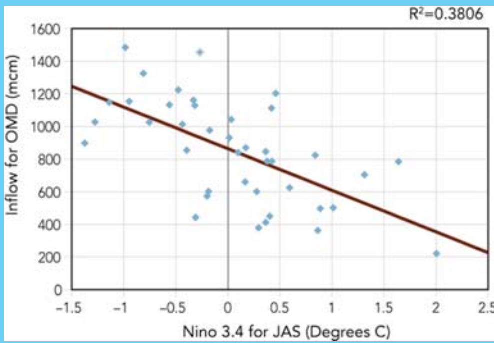

Figure 4.4 Linear regression model between Angat Reservoir inflow during OND and the NINO3.4 index for ENSO during the previous JAS, 1968–2007. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

Developing a statistical forecast model

Once the predictor variables are selected, the next step is to develop a mathematical (statistical) model relating the predictor variables to the predictands of interest (e.g. streamflow). In many cases, the forecast model can have a similar form (e.g. a linear regression model) as the statistical test used to identify the predictor variable, although this may lead to positive biases in skill as discussed below.

Due to the inherent uncertainty in climate prediction, both an expected (mean) forecast value and an estimate of uncertainty about the expected value are desired. Three simple approaches for developing a *probabilistic* forecast model with these characteristics are discussed below.

The first approach is to develop a linear regression model of forecasts, as shown in Figure 4.4. The regression equation for the line in this case is:

$$y_i = \mathrm{a}x_i + \mathrm{b} \qquad \text{(Eq. 4.1)}$$

where y_i is the forecast OND reservoir inflow in year i, x_i is the preceding JAS NINO3.4 index (see Example 4.1), and a and b are model parameters fit to the data (in this example, $\mathrm{a} = -255$ and $\mathrm{b} = 864$). As an example forecast, let $x = +0.5$ C (weak El Niño conditions). This results in an expected (mean) forecast inflow volume of about 740 mcm. However, note that the observed inflows corresponding to NINO3.4 values near +0.5 C are highly variable, ranging from just over 400 mcm to around 1200 mcm Figure 4.4. To include this uncertainty in the forecast, the assumption can be made that errors in the mean forecast are normally distributed with a mean of zero and a standard deviation equal to the standard error of the regression (see discussion in the next section for out-of-sample estimation). Mathematically, the in-sample result is given by,

$$y_i = \mathrm{a}x_i + \mathrm{b} + e_i \tag{Eq. 4.2}$$

where e_i is the forecast error in year i, assumed to follow a normal distribution with mean of zero and standard deviation, σ:

$$e_i \in N(0, \sigma) \tag{Eq. 4.3}$$

where

$$\sigma = \sqrt{\frac{1}{n}\sum_i e_i^2}. \tag{Eq. 4.4}$$

By assuming this distribution for the forecast uncertainty, probabilistic forecast products such as tercile-category[6] probability forecasts can easily be derived by computing the exceedance probabilities of the climatology tercile limit values. For example, let $Q_{0.33}$ and $Q_{0.67}$ be flows corresponding to the terciles boundaries computed from historical data. The forecast probabilities for flows in each tercile category would be computed according to the forecast distribution, assumed normally distributed with a mean of y_i (given by Eq. 4.1) and standard deviation

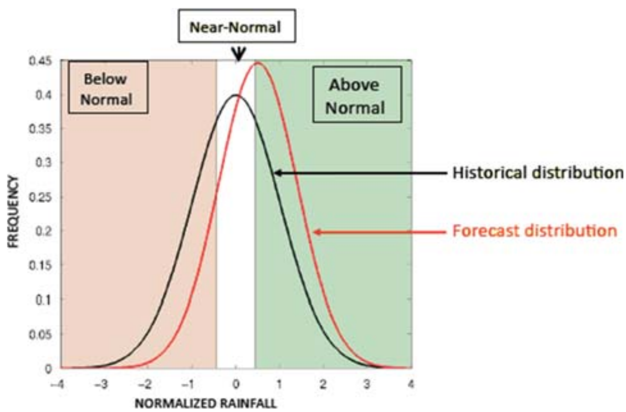

Figure 4.5 Tercile forecast probability density function (PDF).
Historically, the probabilities of above and below normal are 33%. Shifting the mean a half standard deviation to the right and reducing the variance by 20% (because forecasts have lower variance than climatology) changes the probability of below normal to 15% and above normal to 53%. *Source:* Adapted from a figure developed by Mike Tippett, IRI.

[6]There are three tercile categories (below-normal, near-normal and above-normal), defined to have equal likelihood of occurrence in the historical data.

of σ (Eq. 4). Figure 4.5 provides an example of how a tercile probability forecast can be represented.

An alternative approach that does not require the assumption of a particular probability distribution is to sample forecast residual errors using a *k*-nearest neighbor sampling procedure. This is illustrated in Figure 4.6 below. Given a neighborhood of width *h* that contains the *k* nearest neighbors to the observed predictor variable, the residuals are sampled to develop *k* forecast scenarios:

$$y_i = \mathrm{a}x_i + \mathrm{b} + e_j \qquad j = 1, \ldots, k \qquad \text{(Eq. 4.5)}$$

where all terms except e_j are those in Eq. 2 for each year *i*. In this case, however, the e_j is sampled from a distribution defined by the *k* nearest neighbors (see Lall and Sharma, 1996). Together, the *k* forecast scenarios represent an *ensemble* probabilistic forecast for each year. Although the same linear regression forecast model from Eq. 1 is used in this example, the model could instead be based on a nonlinear or a locally weighted regression model. Also, a probability distribution could be fit to the sampled residuals, e_j, representing a hybrid approach for representing forecast uncertainty.

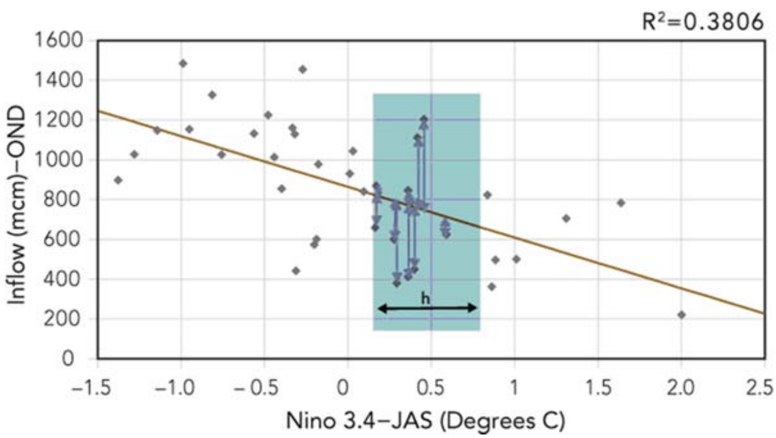

Figure 4.6 Nearest neighbor sampling method for generating a scenario-based inflow forecast for Angat Reservoir.

For a NINO3.4 value of x = 0.5, the k = 12 nearest neighbor residuals (e_j, j = 1, …, k) are sampled to represent the uncertainty in the forecast. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

As a final example of an empirical forecast model, a simple partitioning approach can be used. This would require partitioning the predictor variable into two or more categories (e.g. El Niño, La Niña, neutral), and using the historical observations of predictand corresponding to each of these categories to define a forecast. The forecast could either be represented as an ensemble (set of discrete scenarios) or as a continuous probability distribution fit to the observations. Figure 4.7 illustrates this approach for OND Angat Reservoir inflows based on observed JAS ENSO conditions.

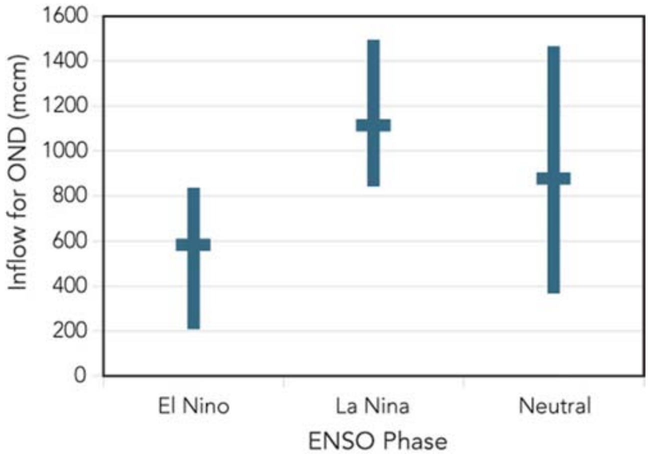

Figure 4.7 Partitioning approach for identifying relationships.
Shown are the ranges of historical OND Angat Reservoir inflows corresponding to three categories of ENSO conditions during the preceding JAS. The horizontal bar shows the mean inflow, while the length of the vertical bars represents the full range of inflow values. Note the significant difference between inflows during El Niño and La Niña events and the very limited overlap. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

Evaluation of forecast model skill

Validating a statistical forecast model and estimating its expected performance (or prediction skill) should involve testing with a set of data that is independent from the data used to fit the model. Evaluating model performance based on the same data tends to give an overly optimistic measure of skill, since the model parameters (e.g. a, b in Eq. 4.1) have been optimized for the training data. If a long data record (e.g. 100 years) is available, a simple approach would be to use a portion of the data (maybe 60–70 years) to fit the parameters of the forecast model, and then use the remainder to validate the model and evaluate its skill.

More systematic approaches involve retroactive forecasting and cross-validation. The basic idea of retroactive forecasting is to simulate the exact forecast procedure (so for each forecast, we use a model that includes only data that would have been available prior to the making of the forecast). This procedure is repeatedly applied to generate a set of forecasts, that can be evaluated to see how well these simulated (retroactive) forecasts would have preformed compared to the actual observations.

As an example of cross-validation (CV), consider a 50-year period of values, 1951–2000. Begin by using 49 years of data (1952–2000) to develop a forecast model to 'forecast' the 1951 value, f_1. This is repeated for 1952, with the data from 1951 and 1953–2000 used to develop the forecast, f_2. The set of cross-validated forecasts (f_i, $i = 1, \ldots, 50$) would then be compared to the corresponding observations (o_i, $i = 1, \ldots, 50$) to evaluate the forecast model performance. For more information on cross-validation and other evaluation techniques, see von Storch and Zweirs (1999). Cross-validation could also be done by holding out more than one year of data at a time. For instance, holding out 5 years at a time, forecasts for the period 1951–1955 would be generated based on data from 1956–2000, then forecasts for 1956–1960 would be based on data from 1951–1955 and 1961–2000, and so on. The standard deviation of the cross-validated model forecast errors may be considered more reliable and used in Eq (4.4) for making probability forecasts (this approach is used in Exercise 2).

Exercise 2: Developing a statistical seasonal inflow forecast model

Exercise 2 allows you to create and validate a statistical model to forecast a three-month seasonal inflow based on hydroclimatic data. You will use relevant climate, inflow and reservoir data for a specific reservoir. The exercise illustrates how to choose an appropriate predictor variable and determine the level of skill that can be expected when applying the statistical forecast model. You will be able to vary the climate predictor value (antecedent conditions or an ENSO index) and observe how this affects the model's forecast output.

Various metrics have been proposed for evaluating the quality of climate forecasts. Perhaps the simplest measure is the coefficient of linear correlation between the expected (mean) forecast value and the observed value, although it is sensitive to outliers. The mean square error (*MSE*) and root mean square error (*RMSE*) are other common ways of evaluating forecast quality. A metric that is closely related to these statistics is the Nash-Sutcliffe efficiency statistic, or ensemble mean skill score (*EMSS*). This statistic is called a skill score because the value of the statistic is scaled by the variance of the observations (climatology) as follows:

$$EMSS = 1 - \frac{\sum (\bar{f}_i - O_i)^2}{\sum (O_i - \bar{O})^2} \qquad \text{(Eq. 4.6)}$$

where $\bar{f}_i$ is the expected (mean) forecast value in year i, O_i is the corresponding observed value, and $\bar{O}$ is the mean of the observations. An *EMSS* value of 1 corresponds to perfect forecasts, and a value of 0 indicates no improvement over climatology, where the climatological forecast consists of forecasting the climatological mean computed over the training period (with the associated probability forecasts derived using the climatological standard deviation). A negative value indicates that the forecasts are actually worse than climatology.

A limitation of the *EMSS* is that it only considers the mean forecast value. Other metrics more appropriately consider the range of probabilistic forecasts. For example, the ranked probability score (*RPS*) and the ranked probability skill score (*RPSS*) are measures of the skill of probabilistic forecasts in the form of multiple ordered categories, such as tercile forecasts (e.g. see Figure 4.5 for more information on tercile forecasts). Mathematically, the *RPS* evaluates the sum of the squared differences in the cumulative probability distribution, so that

$$RPS = \frac{1}{K-1}\sum_{m=1}^{K}\left[\left(\sum_{k=1}^{m} p_k\right) - \left(\sum_{k=1}^{m} O_K\right)\right]^2 \quad \text{(Eq. 4.7)}$$

where K is the number of forecast categories (e.g. high, medium and low), p_k is the forecast probability for the kth point, and O_k equals zero or one to indicate whether or not the observed value is in the kth category. The use of *RPS* results in higher penalties for forecasts farther away from actual outcomes, rather than scoring based on only two categories (hit and miss). The *RPS* can assume a number between 0 and 1, with a perfect forecast scoring 0.

The *RPSS* then measures the relative improvement of using a forecast over using climatology alone. It is computed as:

$$RPSS = \frac{\overline{RPS} - \overline{RPS}_{\text{climatology}}}{0 - \overline{RPS}_{\text{climatology}}} = 1 - \frac{\overline{RPS}}{\overline{RPS}_{\text{climatology}}} \quad \text{(Eq. 4.8)}$$

A perfect *RPSS* is 1, while a score of 0 implies no improvement over using climatology. Negative scores indicate that forecasts performed worse than using climatology.

Although various skill metrics have different relative benefits, each has its own value. Regardless of which technique is chosen, it is critical to determine the skill of any forecast produced. In order to use a forecast model, you should feel comfortable that it appropriately models your system at a level deemed acceptable. Climate-related forecasts will always have some degree of uncertainty, and this should be quantified to the degree possible and taken into account when integrating the forecast in decision making. This will be discussed in more detail in Chapters 5 and 6.

In recent decades, climate scientists and water resources professionals have been trying to collaborate to improve climate-based water supply forecasts. While there are some technical barriers to integrating climate forecasts into these hydrologic models, the primary challenges often arise from perceptual barriers (see Pagano & Garen, 2006 for an exploration of the history of forecast use and challenges in the water community in the Western United States). There is often significant misunderstanding of forecast skill and the effective use of probabilistic climate forecasts.

Lemos *et al.* (2002) offer lessons for improving the cultural perception of forecasts based on experiences in the state of Ceará in Northeast Brazil. In addition to effectively communicating the limitations and skill of the forecast, it is critical to engage with end-users of forecast information to ensure that the information being provided is accessible and appropriate. Stakeholders can differ considerably in their needs for forecast information based on varying vulnerabilities and risk tolerance. In the case of Ceará, although there were early failures in the use and communication of forecast information, "forecasts offer a dramatic opportunity for state and local level bureaucracies responsible for drought mitigation to embark on a path of proactive drought planning" (Lemos *et al.* 2002; p. 503). The regional case below provides an example of climate scientists working with water resources professionals to develop forecast evaluation methods that are most appropriate for stakeholders' needs.

EXAMPLE 4.1: Development of a stakeholder-driven forecast evaluation tool; working with stakeholders to understand their needs and customize forecast evaluation tools to address their concerns

A team of researchers at the University of Arizona's Climate Assessment Program for the Southwest (CLIMAS) in the United States interviewed regional decision makers to understand their concerns regarding using seasonal climate forecasts (Hartmann *et al.* 2002). The researchers worked with a range of water resources managers and other stakeholders in the Southwest U.S. to assess the variety of (i) user needs for seasonal precipitation and temperature forecast information and, (ii) their understanding of various methods of communicating forecast information. One of the key constraints was the perceived lack of forecast credibility and uncertainty regarding previous forecast accuracy. The team identified a suite of criteria for evaluating forecasts and developed a tool to allow stakeholders to choose the forecast evaluation technique most appropriate for their needs. The Forecast Evaluation Tool (FET) is free and publicly available at http://fet.hwr.arizona.edu/ForecastEvaluationTool/.

The FET provides a number of different options to evaluate how well a forecast should be expected to perform, including three types of skill scores and the following statistics (Figure 4.8):

Probability of Detection (POD) – How well has the forecast system been able to warn about upcoming conditions? This tracks how often the forecasts say the right category (e.g.warmer or cooler) is most likely, compared to how often that category has actually occurred.

False Alarm Rate (FAR) – How well can you trust what the forecast says? This criteria tracks how often the category given the greatest probability has turned out "wrong", compared to the how many times that category has been forecast.

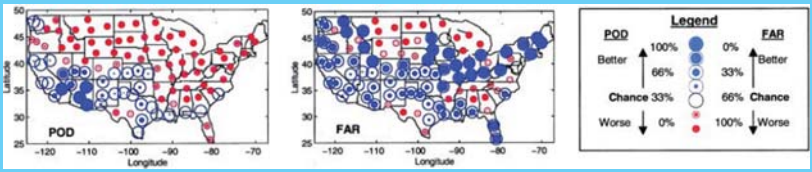

Figure 4.8 Probability of Detection (POD) and False Alarm Rate (FAR) for seasonal precipitation outlooks.

These correspond to the wettest tercile predictions issued during Dec–Feb and covering Jan–May. The blue circles indicate climate outlooks are better than using climatology (red indicates worse). Circle size indicates percent difference relative to potential shown by outer circle. *Source:* FET website and Hartmann *et al.* (2002).

Other options for evaluating the forecast skill vary in the degree of technical knowledge necessary to interpret them. This offers trade-offs between different levels of informativeness versus understandability and allows users to explore a variety of aspects of forecast performance (Hartmann *et al.* 2002). Ultimately, the goal is for decision makers and forecasters to "begin to determine essential forecast attributes, requisite performance thresholds, and relationships among the quality of forecasts and their usefulness in decision making, and ultimately their economic value" (Hartmann *et al.* 2002: 696).

Section 2.2: Dynamical models

A more sophisticated way to develop seasonal climate forecasts is by using dynamical (physics-based) general circulation models (GCMs) of the ocean and atmosphere that are based on fluid-dynamical equations of motion. These are large, complex numerical models that require significant computational resources. A number of models and modeling procedures are used by various agencies around the world. One approach is to first use a model to predict tropical SSTs, and then incorporate these predicted SSTs into an atmospheric GCM to then forecast how the SSTs will affect precipitation and temperature. Models with both ocean and atmospheric components (coupled ocean-atmosphere GCMs) may also be run to simultaneously predict future SSTs and atmospheric conditions. Using these models to make forecasts still requires some statistical calibration to correct for systematic biases between simulated and observed variables. Multi-model ensembles that statistically combine forecast values from different models are employed to further enhance skill. Furthermore, the forecasts from such models can be used to define predictor variables (such as model forecast area-average precipitation) that can, in turn, be used as predictors in conjunction with the regression models discussed above. This is often referred to as a Model Output Statistics (MOS) approach. An example of a probabilistic seasonal forecast for precipitation made at the IRI from a multi-model ensemble of GCM forecasts is shown in Figure 4.9.

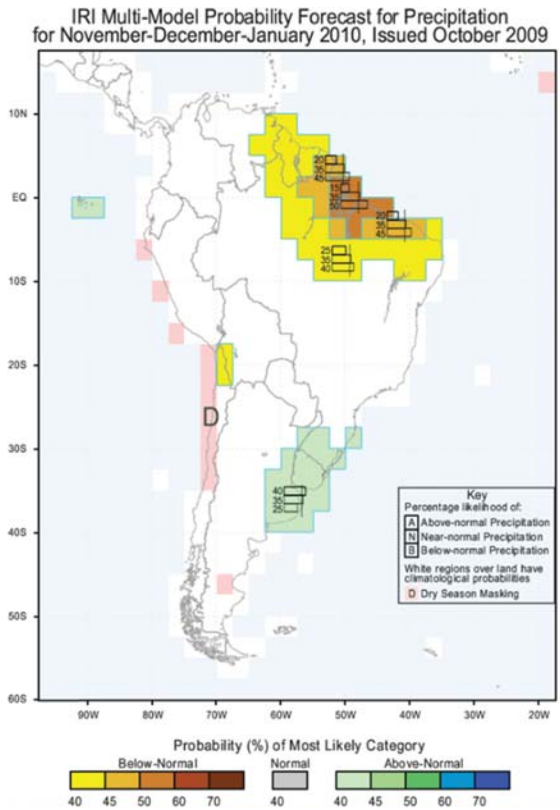

Figure 4.9 An example of a probabilistic seasonal forecast for precipitation made at the IRI.

The probabilities on the map represent the relative likelihood of precipitation falling into three tercile categories: Above-Normal, Near-Normal and Below-Normal. These three categories are determined by ranking the seasonal precipitation over the 30-year period 1971–2000. *Source:* IRI accessed http://iri.columbia.edu/climate/forecast/net_asmt/2009/oct2009/NDJ10_SAm_pcp.html.

In many cases, despite their added complexity, GCM-based approaches do not provide much more skillful seasonal forecasts than those derived from purely statistical methods. Furthermore, since GCMs cover the entire globe, practical computing limitations means that, to date, their resolution (grid size) is often too coarse to be useful for climate forecasts for many watershed scales. To address these limitations, forecasters may nest a high-resolution regional climate model (RCM) within a GCM over the area of interest. This approach can resolve more local detail, including topography and land surface processes. This technique is called "dynamical downscaling". Another approach is to use "statistical downscaling", which involves the application of statistical methods (e.g. linear regression) to relate GCM outputs to weather or climate observations at a smaller scale. These techniques are very helpful for translating the output from GCMs into information that can be used to develop forecasts for a specific reservoir or water system. Figure 4.10 illustrates possible methods for translating GCM-based dynamical model outputs to streamflow forecast.

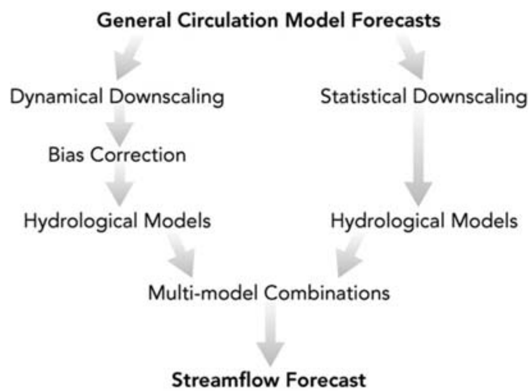

Figure 4.10 Illustration of possible combinations of dynamical and statistical techniques that result in using SST to develop a streamflow forecast.
The GCM forecast input can come from a single model or multiple GCMs. In practice, statistical transformation may be used to shorten the sequence of steps shown, for example, in the right side flow on the diagram, a single statistical transformation may be used to directly translate GCM output into streamflow. *Source:* Adapted from Block *et al.* (2009).

Similar to the statistical forecast methods described above, dynamical model forecasts can be calibrated and refined using statistical methods to provide information that is relevant specifically for water resources management. For example, Block *et al.* (2009) developed multi-model ensemble streamflow forecasts for a water system in Northeast Brazil. They used regional models to downscale GCM precipitation hindcasts, and then fed the results into hydrological models. The researchers found that this technique offers increased skill over other approaches and provides flexibility for improvements at many stages. It is critical to note that experience has shown that enabling real benefits for managing water systems requires that such “tailoring” of forecasts be designed in close collaboration between water resources professionals and climate scientists.

Prediction over longer time scales

As introduced in Chapters 1 and 2, longer time scale variability and climate change can also be very significant for water systems. This chapter has focused on climate and streamflow prediction at the seasonal time scale because of its importance for water resources management and the relatively high degree of skill possible for seasonal forecasts in certain regions. While seasonal forecasts are in principle able to reflect and therefore track these slower time scales through their initial conditions and forcings (e.g. Hamlet & Lettenmeier, 1999), there is also a need to develop longer projections (e.g. decades ahead) of possible future climate scenarios. Predictions at such a scale typically rely on GCMs and RCMs. The Intergovernmental Panel on Climate Change (IPCC) coordinates a wide range of dynamical models to create ensemble projections of possible changes in climate conditions at the global and regional scales based on various scenarios of greenhouse gas (GHG) emissions and future aerosol loadings (Figure 4.11). The IPCC also released a report specifically addressing projections for possible impacts of longer-term climate change on water (Bates *et al.* 2008). In addition to anthropogenic climate change, Chapter 3 (sub-section 4) in this manual also noted the development of information about natural decadal climate fluctuations. The potential to merge information about decadal fluctuations and global change is an active area of research (Meehl *et al.* 2009).

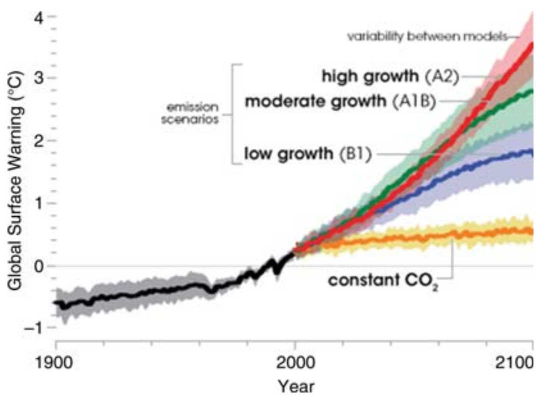

Figure 4.11 IPCC projections of possible global surface temperature warming based on emissions scenarios.

The light colors surrounding each bold curve demonstrate the variability between the models when run with the same emission scenario. This reveals the significant uncertainty arising from both variability in possible emission scenarios and variability between models within a given scenario. *Source:* Adapted from IPCC (2007).

It is important to keep in mind that the IPCC projections in Figure 4.11 should be interpreted only as scenarios rather than forecasts of future expected conditions at any point in time. Although they are not actual forecasts, hypothetical projections based on different scenarios can be useful in understanding how systems might respond to various changes. Chapter 5 provides analysis based on hypothetical synthetic inflow scenarios as a way of assessing how a reservoir system might be affected by different possible changes in inflow conditions. In addition, Chapter 6 introduces the idea that managing variability, including using seasonal forecasts, can introduce additional resilience to water supply systems in the presence of a changing climate. These aspects of Chapters 5 and 6 are examples that highlight how the types of climate risk management approaches discussed in this manual intersect with adaptation to climate change.

EXAMPLE 4.2: Tailoring seasonal forecasts for streamflow in South Africa

South Africa is already hydrologically vulnerable and is expected to become increasingly susceptible to climate-related risks with climate changes and shifts in demographics and land use (Schulze, 1997). Climate scientists both in the country and internationally have been working to develop improved seasonal streamflow forecasts to help water resources managers support agriculture and sectors. Several years ago, Landman *et al.* (2001) developed a real-time operational seasonal forecast using statistical downscaling of a physically-based GCM. They downscaled to the catchment level and then used bias-corrected simulations to achieve categorized (above-normal, near-normal, below-normal) streamflow forecasts that showed skill over short lead-times.

In addition to developing tools and techniques to improve the streamflow forecasts, some of the climate scientists studied the perceived impact of integrating forecasts into decision making on the part of commercial agriculture users (Klopper *et al.* 2006). They found that it is critical to consider the end-user and their needs when developing and disseminating the forecasts in order to address user frustration with limited knowledge and resources.

A group of the climate scientists has continued to work with water resources professionals to improve the forecast models as techniques are improved and technical capacity increases, Landman *et al.* (2009) are producing multi-model ensemble long-range forecasts for the country, working with a multi-model forecasting system developed at the South African Weather Service to produce 3-month operational streamflow forecasts, as seen in Figure 4.12.

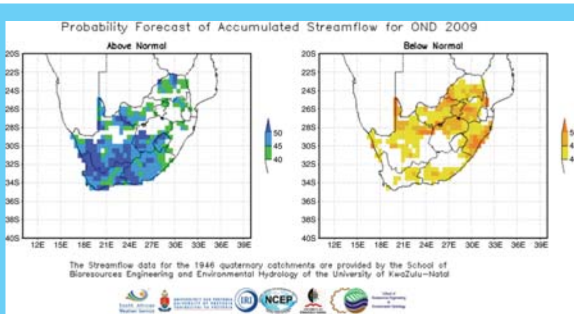

Figure 4.12 Forecast probabilities of above-normal and below-normal streamflow for October-December 2009.
The map on the left shows probabilities for above-normal streamflow, while the map on the right shows probabilities for below-normal streamflow. *Source:* Willem Landman, forecast based on system developed by South African Weather Service.

Section 3: On-line tools and data

Use of the statistical and dynamical climate modeling approaches described above requires a significant amount of data, knowledge and training. Collaboration that includes climate professionals who have expertise in forecasts and associated tools, can be expected to lead to the application of the new climate forecasting technologies in the most robust and relevant ways. Both climate science practitioners and other professionals who rely on climate forecasting can utilize various tools to analyze climate data and aid forecast development. There are a number of free tools available online that may be useful for exploring climate analysis and predictability in various regions. One such resource is the user-friendly Interactive Plotting and Analysis Pages hosted by the U.S. National Oceanic and Atmospheric Administration's Physical Sciences Division (http://www.esrl.noaa.gov/psd/cgi-bin/data/getpage.pl). This section provides a brief introduction to two additional software tools with corresponding data libraries.

Section 3.1: KNMI Climate Explorer

The KNMI (Royal Netherlands Meteorological Institute) Climate Explorer is a freely available web-based software package for climate analysis that includes an integrated library of climate data available on-line at http://climexp.knmi.nl. In applying this tool, the user has the choice of a wide range of climate data, including daily and monthly station data (e.g. precipitation, temperature, streamflow); daily and monthly climate indices (e.g. NINO3.4); 6-hourly to monthly gridded observations and reanalysis data (e.g. pressure fields, SSTs); and monthly seasonal forecasts based on GCMs and historical reconstructions.

The tool includes an option to enter user-defined time series point or field data. Once the user has selected the time series or fields of interest, there are many options for investigating the data, correlating it to other data, and generating derived data from it. While the tool itself is not intended to create forecasts, it offers easy access to climate information and supports exploratory analysis that can help identify appropriate climate predictors. Table 4.1 lists some of the available data that could be useful in water resources management studies.

Table 4.1 Sample of data available on-line for use with the KNMI Climate Explorer.

- Daily and monthly station data (temperature and precipitation)
- Daily and monthly climate indices (e.g. SOI, PDO index, AMO index)
- Monthly observed fields (e.g. SST, sea level pressure)
- Monthly reanalysis fields
- Monthly seasonal forecasts (GCM outputs)
- Monthly and seasonal historical reconstructions (sea level pressure, precipitation, temperature)

Source: *KNMI Climate Explorer, accessed http://climexp.knmi.nl.*

Figures 4.13, 4.14 and 4.15 illustrate some of the data analysis capabilities of the Climate Explorer.

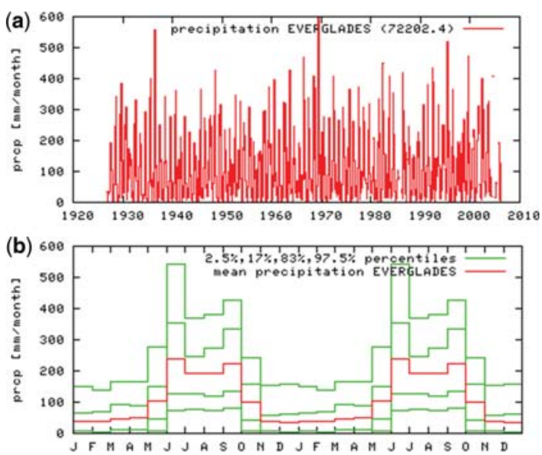

Figure 4.13 Precipitation anlyses using the KNMI Climate Explorer.
Some investigative data analyses using the KNMI Climate Explorer applied to a specific watershed, the Everglades in the United States. Precipitation shown (a) as raw time series, and (b) climatology by month, with selected probability curves. These graphs can be used to illustrate the historical distribution of precipitation for a given system. *Source:* Everglades data from the Global Historical Climatology Network (GHCN) database; KNMI Climate Explorer accessed at http://climexp.knmi.nl/.

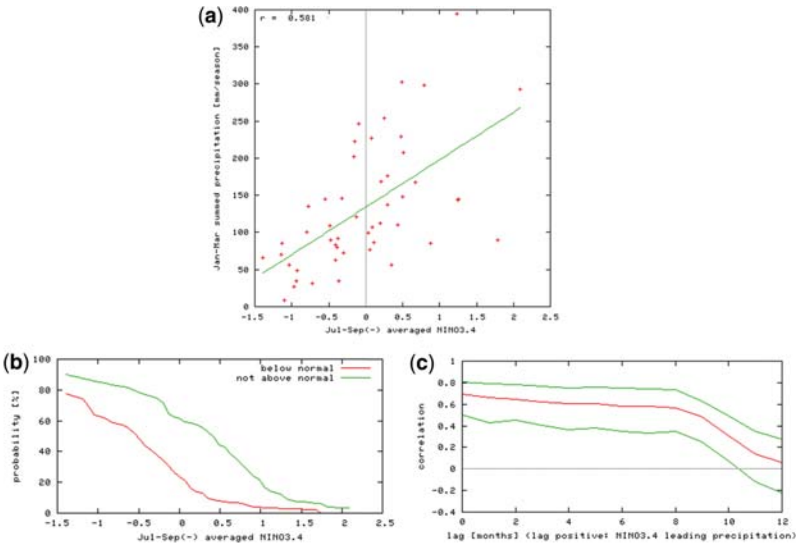

Figure 4.14 Correlation analysis of time series data using the KNMI Climate Explorer.

JFM precipitation (Everglades, United States) and the previous year's ENSO state. Panels show (a) scatter plot, (b) tercile plot, and (c) lag-correlation plot with 90% confidence interval. These curves can help identify the relationship (correlation) between precipitation and climate indicators such as an ENSO index. This can demonstrate the possible strength of climate predictors for hydrologic variability within a system. *Source:* Everglades data from the Global Historical Climatology Network (GHCN) database; KNMI Climate Explorer accessed at http://climexp.knmi.nl/.

Section 3.2: IRI Climate Predictability Tool

The second software tool is the Climate Predictability Tool (CPT), developed by the International Research Institute for Climate and Society (IRI). This software package is designed for assessing predictability and making seasonal climate forecasts and is available for download, free of charge, from the IRI's web page: http://iri.columbia.edu/climate/tools/cpt. This page also has a link to the latest SST data in a CPT-compatible format. The software allows multivariate regression models, including multiple linear regression, principal components regression (PCR), and canonical correlation analysis (CCA), to be easily constructed and visualized. Both PCR and CCA are designed to minimize the dangers of overfitting multivariate regression models that arise with short data time series. CPT uses rigorous cross-validation and retroactive forecast model validation procedures. Many different output statistics and skill scores are included to help evaluate the expected performance of the forecast model. Figure 4.16 illustrates steps in the application of CPT to develop and validate a forecast model.

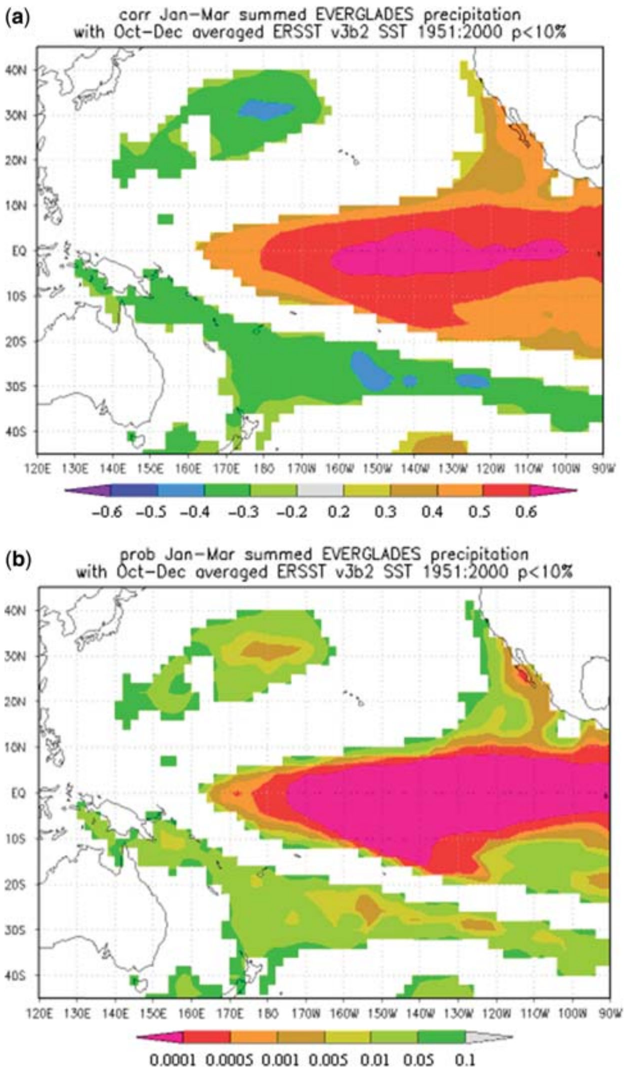

Figure 4.15 Correlation analysis of time series and field data using the KNMI Climate Explorer.

JFM Everglades precipitation index is correlated with OND Pacific SST. Panel (a) shows the correlation map and Panel (b) shows the statistical significance of correlations. For Panel (a), the red and purple colors indicate regions where the SSTs during OND have a strong positive correlation with the Everglades precipitation in the following JFM. For panel (b), all shading is significant at better than 10%, and the redder colors are very highly significant (on the color key, for example, 0.01 = 1% statistical significance). *Source:* Everglades data from the Global Historical Climatology Network (GHCN) database; KNMI Climate Explorer accessed at http://climexp.knmi.nl/.

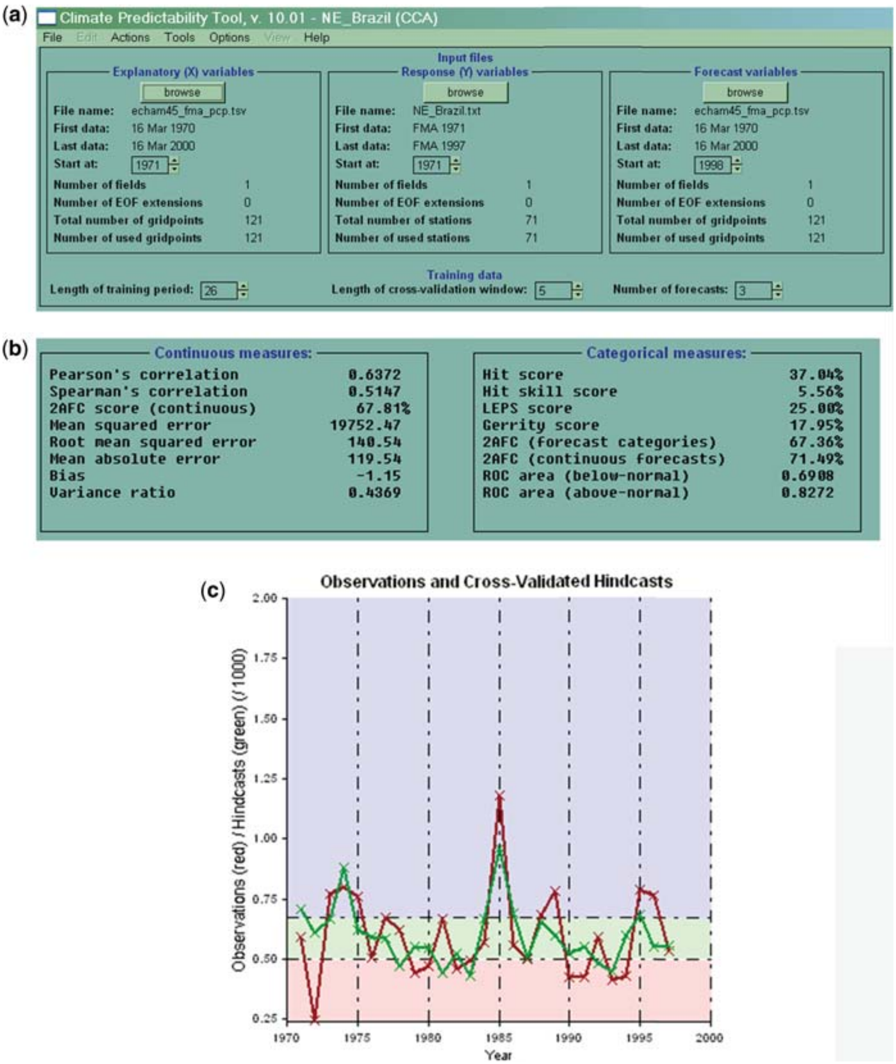

Figure 4.16 Illustration of the application of CPT.
Panel (a) shows the model construction; (b) performance statistics; and (c) the performance graph. Panel (a) shows the page in which the user is able to input the datasets and determine the settings to create the desired statistical model; (b) reveals the statistical output from the model, including multiple techniques describing the skill of the statistical model in predicting precipitation based on the SST input; and (c) provides a graph comparing the observation with the cross-validated forecasts overlaid on colors representing the observed climatological tercile categories (purple is above normal, green is near normal and pink is below normal). *Source:* CPT accessed at http://iri.columbia.edu/climate/tools/cpt.

Users must supply their own data for analysis with CPT. However, IRI hosts the IRI Data Library and provides on-line scripting tools for downloading climate data from the library and formatting it for use with CPT. The web site also includes detailed instructions and a tutorial for using the Data Library. Much of the data available on-line as part of the KNMI Climate Explorer is also available from the IRI Data Library. Figure 4.17 shows various screens of the IRI Data Library interface for an example in which the user constructs and visualizes OND seasonal averages of SST anomalies.

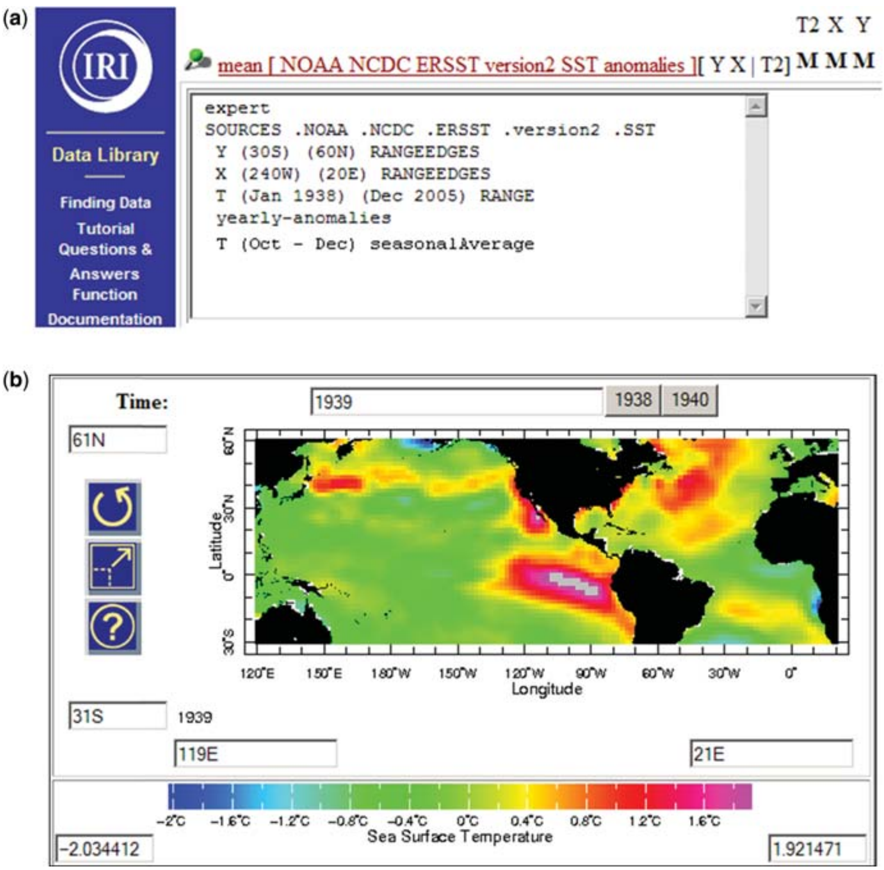

Figure 4.17 IRI Data Library.
Panel (a) shows the scripting interface and Panel (b) demonstrates the visualization of data. These illustrate the ability of users to, create codes to access and work with selected data and develop visualizations of the results. The example script shown constructs seasonal averages of SST anomalies for The script in panel (a) can also be generated automatically from menus, so knowledge of the scripting language is not required to access data. *Source:* IRI Data Library accessed at http://iridl.ldeo.columbia.edu/.

CONCLUDING REMARKS

The topics covered in this chapter provide some background on the type of methods and tools available to make climate forecasts. Basic hydrologic forecast models and those incorporating statistical climate prediction offer simple techniques for translating climate information into useful hydroclimatic forecasts at the seasonal time scale. Although they are more complex and resource intensive, dynamical models are also available and can be used for forecasts at seasonal and longer time scales. Water resources professionals can also utilize online resources to access climate data and use it to develop seasonal forecasts. However, as discussed above, best outcomes are anticipated through collaborations of relevant expertise, including water resources professionals working with the appropriate climate and meteorological agencies when attempting to use climate forecasts for their systems. Climate professionals can help interpret the relevant climate information and work with water resources professionals to determine the best and most appropriate techniques. It is hoped that this chapter can serve to provide a basic foundation to improve that communication.

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Chapter 5

Climate risk management in the water sector

INTRODUCTION

Water resources managers have the critical responsibility of addressing the significant impacts of hydroclimatic variability across multiple time scales. Changes to the climate, demographic trends, land use and water management goals increasingly necessitate moving from static to dynamic approaches to hydroclimatic risk management. Climate risk management (CRM) has evolved as an innovative and effective way to integrate the management of current climate variability and extremes with adaptation to longer-term climate change. The central approach of CRM involves the development of proactive strategies aimed at maximizing positive and minimizing negative outcomes in a given climate-sensitive sector. It is important to move beyond the traditional focus on only negative consequences and explore ways of taking advantage of opportunities. This chapter outlines a CRM-based approach to the assessment and management of hydroclimatic risk with an emphasis on management of water supply systems.

In order to understand the CRM approach for water resources management, it is helpful to be aware of some key terms. While there are not universally applicable or accepted definitions of the terms used in risk management generally, this manual works from the following definitions:[1]

Hazard – 1) the source of a negative effect on a community or system, or 2) the probability of an event that causes failure

Risk – the combination of the probability of a hazardous event occurring and the impact or consequence of that event; risk can increase if either the probability increases or the consequences of a hazard become more severe

Vulnerability – the characteristics of a community or system that cause them to be susceptible to adverse outcomes when exposed to a particular hazard

[1]Definitions can vary significantly between different professional communities, such as those involved in disaster risk reduction and social vulnerability research. The definitions used here are adapted from IRI (2006) and van Aalst *et al.* (2007). See also Hashimoto *et al.* (1982).

Resilience – the capacity of a community or system to recover from an adverse outcome due to a hazard and obtain an acceptable level of functioning

These definitions can also be applied specifically to the context of managing water supply. In this case, a hazard is typically a threat to the water supply system and its ability to function. Risk is, thus, the combination of the consequences of such a threat and its probability of occurring. Vulnerability and resilience can be quantified in terms of whether levels or values over time, $\boldsymbol{X_t}$, exceed a threshold, $\boldsymbol{X^T}$, ("satisfactory values") or fail to meet the threshold ("unsatisfactory values" or a hazard, in some cases). This understanding can also be applied to the concept of reliability discussed in Chapter 2 when considered over $\boldsymbol{n}$ total periods.

Vulnerability:

$$\frac{[\text{sum of positive values of } (X^T - X_t)]}{[\text{number of times an unsatisfactory value occurred}]}$$

Resilience:

$$\frac{[\text{number of times a satisfactory value follows an unsatisfactory value}]}{[\text{number of times an unsatisfactory value occurred}]}$$

Reliability:

$$\frac{[\text{number of time periods when } X_t >= X^T]}{n}$$

With an understanding of these key terms, we can begin to discuss the elements of climate risk management. CRM can essentially be structured as three key components. The first step is to perform an assessment of the hydroclimatic risks and opportunities for a given context. Second, relevant water supply projections should be made by including available climate knowledge and information. The resulting probabilistic water supply projections will often benefit from discussions and collaboration between experts in the water and climate operational communities. Finally, practitioners make management decisions based on the results from the first two steps while also explicitly considering the role of uncertainty in the system. This chapter is organized around these three elements; first Section 1 describes the elements in more detail, then Section 2 explores the application of the CRM approach to a stylized example based on the management of a multipurpose reservoir.

Section 1: Components of the climate risk management approach

Step 1: Assess hydroclimatic risk

Chapter 2 described tools and approaches for hydrologic analysis in water resources management with an emphasis on predicting and managing water supply and availability. Chapters 3 and 4 examined climate variability and change and how understanding both can impact hydrologic supply projections. The first step of climate risk management is to assess the impacts of changes in climate across all time scales on water resources. This necessitates knowledge of both historical climate information and the resulting consequences in the target water system.

Developing the appropriate knowledge requires a dialogue with climate professionals as well as the stakeholders affected by or engaged in the water management process. Climate scientists and meteorological agencies can help supplement and interpret relevant climate information. Engaging stakeholders can both ensure that relevant impacts are considered and keep stakeholders aware of the process.[2] By gaining a more robust understanding of these hazards and impacts, you can begin to determine the hydroclimatic risk for a given system.

While this manual focuses on the impacts of climate on the system, with an emphasis on consequences for water supply, it is important to recognize that climate is one of many factors affecting the system. When projecting future risk scenarios for a given system, possible changes in population growth, user demand and land use should all be considered and integrated into any comprehensive risk assessment. Although these topics are generally beyond the scope of this manual, Appendix 2 reviews some basic techniques for forecasting water demand.

Additionally, climate information can sometimes significantly affect users' decisions and the aggregate demand on a system, depending on the policy landscape and the extent of climate knowledge. For example, farmers' decisions are often strongly affected by risk and may thus change based on whether, for example, insurance, options contracts or drought-resistant crops are available. The presence or absence of such mechanisms may largely determine the degree and distribution of climate-related impacts on a system and its users.

Acknowledging that these demand-side factors are present, you can proceed to assess the hydroclimatic risk for a system across time scales. Since risk involves both the impact of a hazard and the probability of the hazard occurring (or the expected gain from an opportunity and the probability of realizing the opportunity), your assessment must consider both the impact and probability. The questions below provide a general guideline for what to consider when performing this assessment.

What key climate-related challenges does the system currently face?

These challenges might include moderate or severe droughts, flood events, variable flows or others that are particularly disruptive to the system. This assessment is based on climatology (historical observed variability) and current system

[2]As an example, the Florida Division of Water Resource Management in the U.S. developed the "Framework for Action: Water Management and Climate change in Florida" to support the state and local water management agencies in understanding how to address the likely impacts of climate change, including references to using seasonal climate information. The report was based on research and interviews with local water managers. See Bolson and Swihart (2008).

characteristics, such as land use, population, and economic factors. It is important to identify the hazards historically associated with climate variability for the system while also understanding that the same type of climate event might have a more or less severe impact based on evolving non-climate characteristics of the system over various time scales.

What damages occur as functions of these events?

Having identified the climate-related hazards, the impacts on the system need to be addressed. This includes an analysis of the distribution of impacts (e.g. spatial or sectoral) and a determination of whether there are distributional effects from these events. Impacts on both the human and environmental systems may be relevant.

The method of valuing consequences may differ. For example, economic valuation of consequences (e.g. foregone profits, direct costs associated with switching to another water source) will be appropriate in some cases. However, in the case of severe consequences (e.g. famine), economic valuation alone may not be sufficient, as the social consequences may far outweigh direct economic costs. While we consider this evaluation to be a matter of national and international policy, and thus focus on the direct economic valuation of consequences, we stress the importance of designing systems which are resilient to catastrophic failure.

It may be important to determine local thresholds that determine the extent of climate-related consequences (e.g. see the conceptual Figure 5.1). While some water users can easily adapt to small reductions in water supply with little or no adverse effects, others may face significant damages from even the smallest supply variations. The vulnerability across different users might lead to an aggregate threshold level and expected reliability for the system.

Figure 5.1 Risk Threshold.
This figure is a stylized representation of a range of possible outcomes following a normal distribution (bell curve). There exists an outcome below which the system faces a hardship or, if the outcome is even more extreme, a crisis. This is shown as the 'Risk Threshold'. The white space to the right of the Risk Threshold can be considered baseline outcomes (i.e. outcomes that result in neither harms nor benefits). An individual outcome leading to a hardship or crisis has lower probability than an outcome resulting in baseline conditions. If the x-axis represents a measure of societal outcomes, the Risk Threshold might represent a minimum flow necessary to meet minimum user needs from a reservoir. Less streamflow results in a hardship, and very low streamflow, while lower in probability, results in more severe crisis conditions.

Are there potential opportunities due to climate variability and change?

Although a major concern is the possible negative impacts from climate variability and long-term change, some climate outcomes also bring opportunities for benefits (see conceptual Figure 5.2). An example where climate has clearly served to provide an opportunity is where the annual cycle produces distinct rainy seasons (i.e. a lack of variability in climate between seasons within a year would be disastrous for most crops). Additionally, a shift in phase in multidecadal variability within a system could lead to improved average climate conditions for some sectors. For example, if the current phase was increasing the probability of drought conditions, a phase shift might reduce drought occurrences on average. It is important to remember interactions of the various forms of climate variability and also assess the possible impact of long-term climate change. The latter might also offer some opportunities (e.g. increased average precipitation in arid regions). Assessments should take into account the varying opportunities and risks across sectors and across (or even within) regions, along with their uncertainties.

Figure 5.2 Opportunity Threshold.
Similar to Figure 5.1, this figure represents a normal distribution of possible outcomes. Here, the emphasis is on the outcomes to the right of the baseline outcomes represented by the white space. These represent opportunities for benefits that result in improved conditions relative to the baseline. The 'Opportunity Threshold' shows the outcome above which benefits can arise. If the x-axis represents a measure of societal outcome, the Opportunity Threshold might represent a flow above which hydropower could be generated in a system. Here, the assumption is that all outcomes above the Opportunity Threshold result in benefits. Based on this figure, benefits occur with the most probable outcome (i.e. the mean streamflow or the peak of the distribution).

Are there opportunity losses due to decisions made to avoid current climate risks?

Water resources managers are typically quite risk averse, meaning that they would prefer an option with less uncertainty but possibly a lower net benefit over an option with greater uncertainty but a higher possible net benefit. Thus, managing to minimize climate risks can decrease the net benefit and result in lost opportunities (e.g. greater release for hydropower generation). Identifying these lost opportunities reveals increased possible benefits from improved climate forecasts.

Example 5.1: Shortfalls – Costs and lost benefits

In general, the economic costs (or losses) associated with system failure are simply the benefits lost by not having more water to apply to various uses. This concept is illustrated in Figure 5.3, which shows a price-quantity demand curve. Assuming the price of water appropriately reflects the cost of the water delivery, the shaded area above the price and below the demand curve represents the net benefits to consumers. If water supplies are restricted from quantity Q to quantity *Q'* due to scarcity, only a modest amount of net benefits is lost as users will first forego the lowest valued uses. Additional net benefits would, of course, be lost if the price also increased.

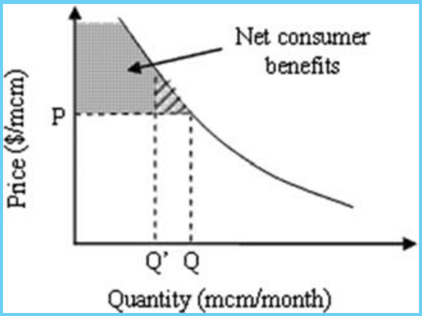

Figure 5.3 Water demand, price and consumer benefits.
Water demand curve and consumer benefits of quantity Q at price P (shaded). If the quantity is restricted to Q**'**, and the price remains the same, the benefits lost are indicated by the hatched area (triangle with diagonal lines).

If water users have access to other, typically more costly, water supply sources, net benefits may be estimated as the cost avoided by not having to rely on the higher cost source. This concept of "cost avoided" is typically used to value hydroelectric power generation whenever fossil fuel plants have excess capacity. A similar approach could be used for agricultural water use, if the alternative to surface water deliveries is to pump groundwater, for example. If no alternative irrigation source is available, the consequences of water delivery shortfalls can be evaluated as reduced profits, perhaps estimated by a mathematical programming model such as the example in Appendix 2.

Have the occurrences of hazard events over the historical record followed identifiable patterns?

The initial step is to determine recurrence periods for relevant climate events over the historical record. For example, analysis might reveal how frequently the system has experienced severe droughts. It is also important to examine whether there is a spatial or temporal structure (or pattern) in the historical hazard occurrence. This might include variability across various time scales (intraseasonal, interannual, decadal) or longer-term trends.

The main purpose at this point is to recognize variability in the climate system and how it has affected hazard probabilities in the past. You are not yet making forecasts or projections about future scenarios. This analysis reveals the probabilities that have determined system risk up to the current period. The understanding of historical climate variability at different time scales also suggests the key components to consider in developing projections in future steps. This can include identifying appropriate predictors that can help you make simple forecasts of possible shifts in the probability distribution of supply in the system (e.g. shifts due to ENSO phases).

How sensitive is the system to hydroclimatic variability and change?

Hydroclimatic conditions affect a water system's ability to meet user demands. Climate variability, thus, has a significant impact on whether the system fails or is able to meet the demand. Different water systems have differing levels of sensitivity to this climate variability. As discussed in Chapter 2, the expected reliability of a reservoir system describes the likelihood that it will be able to meet some level of user demands. Thus, a system's sensitivity to changes in the climate can be measured by changes in reliability.

Analysis and answers to the previous questions in this section provide data on historical climate variability and probabilities associated with various climate outcomes, viewed as hazards. This information can be translated into reliability given certain thresholds (e.g. reservoir levels) appropriate for the given system. It is then possible to calculate how reliability has changed in the past and also determine how patterns of climate variability affect reliability (e.g. see the conceptual Figure 5.4).

If climate conditions and the historical variability were expected to continue into the future without any changes, you could model the expected reliability based on past experiences. However, this assumes that you are aware of all forms of variability and have been able to model them with a high degree of accuracy. If the historical record is too short to capture the full range of climate variability (and this is not uncommon), the results of the analysis can be significantly biased due to sampling variability. In addition, this does not take into account the possible nonstationarity of the system.

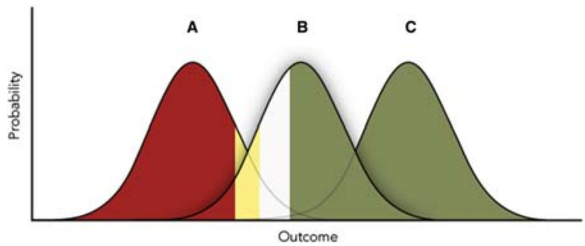

Figure 5.4 Managing risks and opportunities.
This figure demonstrates a system's sensitivity to changes in the distribution of possible outcomes, based on a system's risk and opportunity thresholds (as shown in Figures 5.1 and 5.2) and the degree to which the distribution can change. 'B' represents the distribution of outcomes under normal conditions. 'A' illustrates a situation in which the likelihood of negative outcomes increases, while 'C' demonstrates a shift toward more probable positive outcomes. Managing risks and opportunities requires an understanding of the relationship between thresholds for a system and the shifting outcome probabilities. As an example, these can be viewed as distributions based on possible inflow forecasts, where 'A' is a shift toward drought conditions and 'C' is a shift toward higher inflows (assuming all excess inflows could be used positively, e.g. to create hydropower). These would result in decreased reliability for conditions shown in 'A' and increased reliability for conditions shown in 'C'.

In order to address these concerns and appropriately assess the sensitivity of the system, it is best to model reliability based on both historical data and scenarios of possible future climate conditions. These scenarios can include conditions that fall outside the historical range, since historical knowledge is limited and nonstationarity might lead to significant hydroclimatic changes. You are not yet making projections of what climate conditions are actually expected to be – you are only creating scenarios of possible future conditions to learn about the sensitivity of the water system. This scenario approach is also discussed by Dessai *et al.* (2009). The scenarios can be combined with vulnerability thresholds determined in previous steps. If the vulnerability thresholds are based on changes in reliability, the scenario approach can help shape reliability thresholds for the system.

Step 2: Make probabilistic water supply projections incorporating climate information

Once you have established various scenarios and assessed historical hydroclimatic risk for your water supply system, a route to enhanced benefits is to narrow the range of likely future outcomes. While all outcomes in your full array of scenarios might be possible, you can use climate forecasts and knowledge as discussed in previous chapters to assign probabilities to the various outcomes when reliable climate information is available. The resulting probabilistic forecasts can be combined with an understanding of the system sensitivity to improve assessment of possible future risk and help decision making.

Previous chapters in this manual have explored a variety of approaches to predicting climate and forecasting water supply. The information on statistical and dynamical forecast models in Chapter 4 can serve as a foundation for developing these forecasts. For example, if the system responds somewhat predictably to ENSO phases, you may be able to use an appropriate SST anomaly index in a linear regression model to help forecast likely conditions for the coming season. Depending on the system, available data, and the human and financial resources available, a dynamical model might also be appropriate. In developing the forecasts, you should also collaborate with climate scientists and professionals (e.g. staff from the national meteorological agency) who may be able to help identify relevant climate predictors and develop appropriate techniques for the local system. The climate-based forecasts can then be combined with the tools described in Chapter 2 (e.g. flow-duration analysis and yield-reliability curves) to develop a range of useful probabilistic water supply projections. The following considerations should also be taken into account to encourage the most effective use of climate information.

Consider variability across all time scales

The projections should, as much as possible, span the time scales discussed in Chapter 3. In addition to seasonal and decadal variability within the climate system, longer-term trends might have significant consequences for the system. The collection of tools and models for forecasting climate at various time scales described in Chapter 4 can be used to identify likely future scenarios and probabilities associated with each. However, it is critical to supplement the introductory information in this manual with consultation with climate professionals and relevant meteorological agencies. There are many variations on the basic techniques presented for identifying climate variability at various time scales and translating this information into useful forecasts.

Consider uncertainty

There will always be remaining uncertainty, and this needs to be assessed so that it can be addressed and integrated appropriately into management options (as discussed in Step 3). Based on location and climate characteristics, there may be significant variation in the ability to make climate predictions. For the same system, forecast skill might vary significantly across time scales. It is critical to be aware of the predictive capacity for a given system and the uncertainty associated with any predictions. The probabilistic nature of climate forecasts reinforces the idea that they are neither guaranteed nor absolute. This uncertainty plays a significant role when integrating the climate information into decision making, and you should explicitly assess the uncertainty of any forecasts you consult.

The approach to assessing the forecast uncertainty depends on the techniques used to create the forecast and the projected time scale. For example, if a seasonal forecast has been developed using a statistical model, a cross-validation technique (as described in Chapter 4) can be used to understand and quantify the uncertainty in the model. With complex dynamical and GCM-based models and projections over longer time scales (Meehl *et al.* 2009), it is best to consult climate professionals to determine the uncertainty and errors present in the model. Some of the key discussion points regarding longer-term climate projections that include the effects of increasing greenhouse gases and other anthropogenic influences include,

(1) the climate model's ability to reproduce climatology in the region;
(2) whether the model captures the observed regional trend in 20th century climate;
(3) the extent to which there is a well-established physical basis for the model's forecasts;
(4) the degree of agreement between different models; and
(5) the extent to which natural multidecadal variability impacts the region.

Discussing these topics and validating forecast models can show where the model made errors and help understand possible weaknesses in the specific GCM, contributing to assessments of uncertainty in projections.

Step 3: Determine a portfolio of options to manage hydroclimatic risks

The forecasted hydroclimatic risk determined in the previous two steps serves as the foundation for developing a portfolio of options to mitigate the risk and take advantage of possible opportunities. It is critical to realize that, while a probabilistic forecast provides information about the likelihood of particular climate events (such as droughts), surprises can still happen, even if they are very unlikely. For this reason, it is particularly important to consider ways to manage the impacts of possible climate events that do not necessitate new investments in infrastructure. The reasoning is as follows: if an event is not very likely to occur, it is typically not worth making major investments to manage the impact. However, it still makes sense to try to avoid the negative impacts of that event, if possible. Thus, finding solutions that can be called upon only when needed is an efficient way to manage the impacts of unlikely events.

Another consideration in managing hydroclimatic risks is the need for redundancy. If a water supply system consists of a single source, any impact on that source leaves the system vulnerable. While it may not be economically efficient to build new infrastructure to tap new sources, other opportunities may exist. The suite of risk management options might include economic instruments (such as insurance or water banks), infrastructure modifications, or integrating seasonal forecasts into decision making, among many others. Together, these approaches are termed a "portfolio" of options because they consist not of a single solution, but rather a range of possibilities – each of which may be the best choice in a particular circumstance (conceptually introduced in Figure 5.5). Chapter 6 provides additional information on some of these techniques for managing hydroclimatic risk.

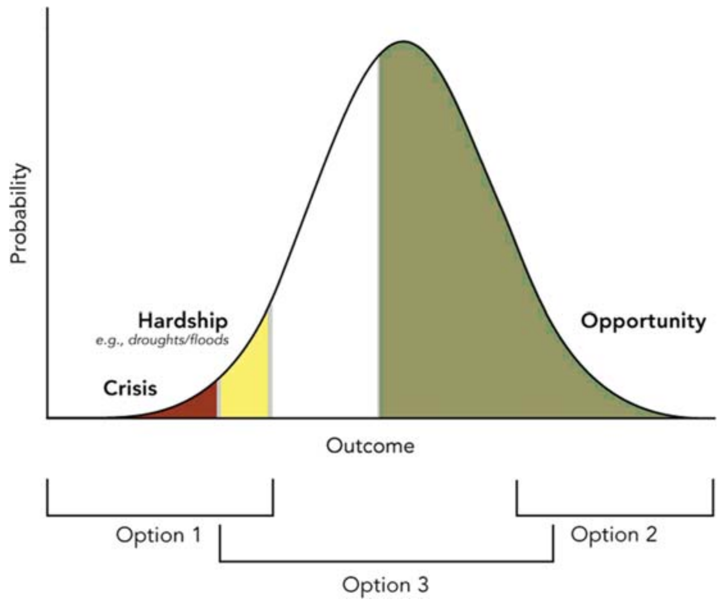

Figure 5.5 Establishing a portfolio of options in climate risk management.
Given the normal distribution (bell curve) of possible outcomes shown in Figures 5.1 and 5.2, this figure demonstrates that different management or policy options are often designed (or only able) to address a certain subset of outcomes. Each option represents a different approach to managing risks and opportunities, and the figure demonstrates the trade-offs associated with each. For example, 'Option 1' focuses on the possible hardship or crisis outcomes, perhaps ensuring that the system experiences the equivalent of baseline conditions (white space representing outcomes that are neither harms nor benefits) even if the outcomes are below the Risk Threshold (see Figure 5.1). 'Option 2' is intended only to take advantage of possible benefits (e.g. a policy that only addresses reservoir releases for hydropower, but does not account for drought or flood conditions). 'Option 3' covers average outcomes and those that result in baseline conditions, while also addressing some range of both possible negative outcomes and possible benefits.

Below are some of the key considerations when developing a portfolio and determining the most appropriate solutions.

Consider planning and operational approaches

The risk management solutions available depend partly on the timeframe for action. Near-term operational options will most likely assume fixed infrastructure and some level of sunk costs (those that have already been allocated and cannot be recovered). Possible planning solutions, on the other hand, can include decisions regarding infrastructure and system design. Climate information should be integrated into decision making at the appropriate time scale to inform options most effectively. Projections of long-term climate change may have little value at the operational level for current practices. However, such projections might inform planning decisions as well as the framework under which operational decisions are made in the future (i.e. whether expected climate changes will necessitate more flexible operational policies).

Assess possible trade-offs

Limited human, financial and natural resources lead to trade-offs in almost all decisions in water resources management. Water managers must seek to understand and assess possible benefits or consequences of their decisions within the context of these resource constraints. Uncertainty makes such assessment even more difficult, but can also increase the importance of decision outcomes. For example, hedging against a possible drought by maintaining high reservoir storage levels might result in increased flood risks. At the other end of the spectrum, managing to avoid floods can increase the possibility of water shortages. There is also often a trade-off between increasing expected reliability for a system and increasing possible benefits from water allocation. Improved climate information and projections of likely futures may help shift the reliability scenarios. While this does not eliminate the necessity for trade-offs, it can improve the long-term frequency of achieving positive outcomes. Integrating thresholds of "acceptable" costs into decision making can help water managers balance trade-offs. You can explore this concept in Exercise 3.

Exercise 3: Assessing risk for a multipurpose reservoir using a water allocation scheme and simulated inflows

Exercise 3 broadens the scope of risk assessment beyond simple reliability analysis based on the historical record. Here you will consider a realistic set of reservoir operating rules and makes water allocation decisions. You will then apply stochastic modeling to simulate various future seasonal inflow scenarios over a 40-year period. This will allow you to examine the potential effects of multidecadal climate variability and/or long-term trends on the system reliability. This exercise also includes a module that illustrates the possible economic consequences of water supply shortfalls.

Consider the impact of uncertainty

Step 2 included uncertainty assessments for the target water system and any available hydroclimatic forecasts. It is necessary to understand the uncertain nature of probabilistic forecasts in order to appropriately assess your suite of options. Rather than planning for a specific outcome, the most appropriate approach often requires planning for a set of scenarios. While the likelihood of a specific outcome might be higher than the likelihood of another, both are possible and should be considered in decision making. This uncertainty may lead to more flexible approaches and policies, with less emphasis on rigid options that leave little room for alternative outcomes. A flexible, adaptive plan might also increase the capacity to take advantage of possible opportunities from better than expected outcomes. Of particular importance is to consider the effects of low probability but high impact events on the system when actions are taken based on a forecast. For example, if the forecast leads you to expect more water, are there ways to mitigate the effects of an unlikely severe drought? This is important to consider because sometimes the anticipatory actions based on a forecast may leave a system more exposed to the "down-side risk", or the risk associated with the less likely, but still possible, climate extreme. Chapter 6 explores some of the techniques and tools designed to address hydroclimatic uncertainty in water supply systems.

Section 2: Example application of the climate risk management approach

To illustrate the main components of the climate risk management approach presented in this chapter, we perform a risk assessment with synthetic scenarios for a stylized multipurpose reservoir. The nature of the seasonal predictability as well as many of the specific management options and variable magnitudes are informed by the Angat Reservoir in the Philippines. In this example, we focus on the risks associated with shortfalls in water supply based on hydroclimatic conditions. While we focus on sensitivity to shortfalls and base the analysis on a specific type of reservoir, the techniques and approach can be generalized to be applicable for other contexts, locations and needs.

Step 1: Assess hydroclimatic risk

For this example, we highlight the assessment and management of shortfall risks that occur when there is inadequate water supply to meet needs. While a shortfall might occur due to extended drought conditions, it can also occur under other conditions. We determine that a shortfall occurs if the reservoir level is not above a given threshold level at a certain point in time. This is the basis for determining the reliability of the reservoir; reliability measures the expected probability of meeting or exceeding the threshold (i.e. reliability measures the likelihood of avoiding a shortfall). For our assessment, we focus on inflow in a critical 6-month period starting in October and ending at the end of March. The level at the end of March is used to determine whether a shortfall has occurred.

What key climate-related challenges does the system currently face?

While the system might face a variety of hazards, we focus only on shortfalls in this stylized example.

What damages occur as functions of these events?

Shortfalls and drought events are often considered most damaging to the system. In a typical priority-based multipurpose system, agriculture is often given low priority. For droughts or shortfalls in these systems, irrigation might be significantly curtailed or stopped. Municipal water may also be rationed and there would be limited releases for hydropower. These can result in crop losses, loss of life, and significant economic impacts.

The economic impacts can be complex. If shortfalls in irrigation water allocation are known in advance, irrigators can plan accordingly by reducing the area planted or selecting more drought-resistant crops. In this case, reductions in economic benefits are roughly proportional to the magnitude of the shortfall (i.e. a 10% reduction in area planted corresponds to a 10% reduction in benefits.) If shortfalls are not planned for, economic losses occur due to plant stress and reduction in yield, which typically occurs as a nonlinear function of the shortfall. For example, a 10% shortfall may lead to a 10% reduction in yield, and a 20% shortfall may lead to a 30% reduction in yield. In practice, the effects of irrigation shortfalls also depend on the timing of the shortfalls (e.g. early in the growth stage or near harvesting), as well as numerous climatic variables, including precipitation, temperature, and humidity.

Are there potential opportunities due to climate variability and change?

While it is difficult to find opportunities in droughts or shortfalls themselves, changes in climate variability or longer-term trends might reduce these hazard occurrences. As suggested earlier, if the current phase of some form of decadal variability were increasing the probability of drought conditions, a phase shift might reduce drought occurrences on average. In the case of possible increased shortfalls, the opportunity arises in the ability to forecast these occurrences in order to plan and manage for them appropriately. In addition, predictably wet years might present the opportunity to be more ambitious in terms of water use (e.g. expanded irrigation, hydropower, etc.).

Are there opportunity losses due to decisions made to avoid shortfalls?

Opportunity losses may occur for both irrigation and hydropower users if decisions had been made expecting conditions to be drier than actually occurred. Irrigators may have unnecessarily reduced the area planted or invested in crops that are more drought-resistant than necessary. Hydropower generation might have been needlessly curtailed if water supplies are significantly higher than initially projected.

Have the occurrences of hazard events over the historical record followed identifiable patterns?

Analysis of climatology and global climate indicators reveals that the monsoon season in the area of this reservoir tends to be drier than normal during years exhibiting El Niño conditions, and wetter than normal during years with La Niña conditions. As shown in Chapter 4, we can create a figure showing the differences in inflows conditioned on ENSO conditions (Figure 5.6).

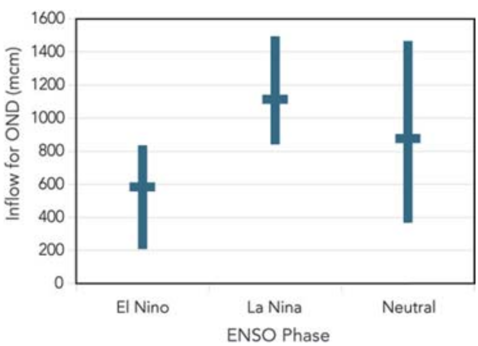

Figure 5.6 Partitioning approach for identifying relationships.
Shown are the ranges of historical OND Angat Reservoir inflows corresponding to three categories of ENSO conditions during the preceding JAS. The horizontal bar shows the mean inflow, while the length of the vertical bars represents the full range of inflow values. Note the significant difference between inflows during El Niño and La Niña events and the very limited overlap. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

Based on this information, we can also generate probabilistic distributions of inflows for the OND period (Figure 5.7).

At this stage in the analysis, these probability distributions are viewed as indicating that there can be systematic fluctuations in inflows. As part of the risk assessment, the sensitivity of the system to such fluctuations can be investigated, contributing to overall information on the vulnerability of the system to climate fluctuations (see sub-section 2 of this chapter). Figures 5.6 and 5.7 can also be used as a simplified forecasting tool if the phase of ENSO is known, as described in Step 2 below. Although not described here, it would also be important to assess whether other forms of climate variability affect this system and introduce other systematic patterns in the flow records.

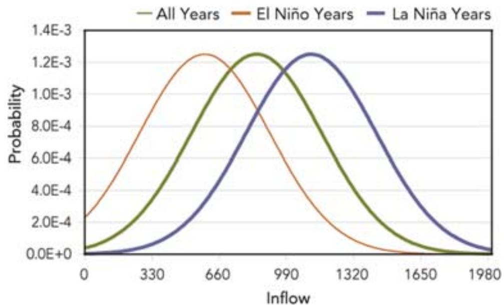

Figure 5.7 Probabilistic three-month (OND) inflow distribution for the Angat Reservoir based on mean inflow across all years, in El Niño years, and in La Niña years.

Each distribution is constructed using the mean across appropriate years and the standard deviation for the entire historical period. Although there is overlap, the El Niño conditions result in reduced average precipitation and inflow, while La Niña conditions result in higher average inflows. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

How sensitive is the system to hydroclimatic variability and change?

In order to understand the system's sensitivity to hydroclimatic changes and nonstationarity, we can assess the impact of various scenarios on the system reliability. This approach is aligned with the methodology that is discussed in detail in Dessai *et al.* (2009a, b). For these simulations, we assume the monthly water allocation scheme for this multipurpose reservoir remains constant from year to year and use a stochastic simulation approach (statistical time series model) to simulate multiple inflow traces for the six-month period (Oct–Mar) under various scenarios. Reliability is then calculated based on the percent of simulated inflows for each scenario that result in reservoir levels at or above a given threshold at the end of March.

We begin by assessing the changes in the system's expected reliability based on different initial storage levels. We can then broaden the analysis to include simulations of ENSO phases to understand how El Niño or La Niña conditions might affect reliability. The simulations considering ENSO phases use the appropriate probability distribution for OND inflow shown in Figure 5.7 above. The inflow for the JFM period for all simulations is always sampled from a climatology-based distribution. In other words, ENSO phase is not considered for the JFM period (this approach may not be appropriate in all systems and is offered here for simplicity in introducing the concept). The reliability estimates are given in Table 5.1 and shown graphically in Figure 5.8.

Lower reliability values reveal that the system is expected to suffer from increased frequency of shortfalls. The above results suggest that the system is sensitive to initial storage levels and particularly sensitive to changes in the interannual variability such as ENSO phases.

Table 5.1 Estimates of water supply reliability based on the inflow across all years, in El Niño years, and in La Niña years.

Initial Storage (mcm)	All Years (3-month inflow mean = 850 mcm)	El Niño Years (3-month inflow mean = 589 mcm)	La Niña Years (3-month inflow mean = 1112 mcm)
190	70%	43%	92%
195	77%	47%	94%
200	84%	57%	97%
205	91%	71%	99%
210	95%	80%	100%
215	97%	89%	100%

Reliability is based on the percent of simulations in which the reservoir level is above a given threshold (lower rule curve) at the end of the period over 100 simulations using the corresponding mean inflow value and initial storage. Source: SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

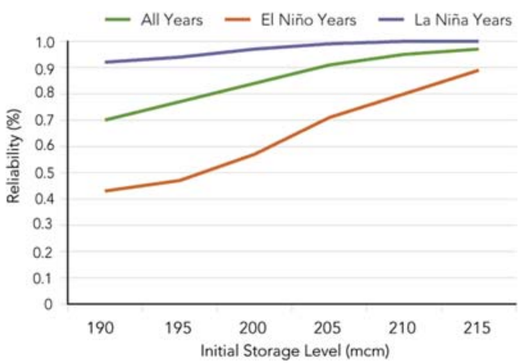

Figure 5.8 Reliability comparison based on simulations using inflows from the corresponding ENSO category and initial storage level.
Reliability is based on the percent of simulations in which the reservoir level is above a given threshold (lower rule curve) at the end of the period over 100 simulations using the corresponding mean inflow value and initial storage. *Source:* SST data from NOAA NCDC ERSST v.2 (Smith & Reynolds, 2004); Angat inflow data from Philippines National Power Corporation.

Next, we can consider two additional climate phenomena to illustrate the potential effects of (i) slowly varying (decadal-to-multidecadal) climate fluctuations and/or (ii) systematic long-term change in the climate. We use hypothetical synthetic inflow scenarios. This concept was introduced in Chapter 3, generating inflow scenarios for the remainder of a given season (e.g. see

Figure 3.2, Chapter 3). Now we generate multiple year inflow scenarios based on plausible climate changes and multidecadal variability in the climate system (this statistical approach to scenario creation for risk assessment is discussed in more detail in Siebert & Ward, 2011). After generating the inflow scenarios, we assess the sensitivity of the reservoir management system to each scenario. Since OND dominates the October–March inflow total, the illustrations here apply the trends and multidecadal variability only to the OND inflow, and unchanged historical climatological inflow is always assumed for JFM. This allows illustration of the concepts. In subsequent more detailed assessments the complete October–March inflow may be modeled. This simplified approach also allows consistency with the ENSO-based results (which also confined perturbations to OND inflow).

First, we simulate seasonal inflows assuming a long-term trend in the climate (e.g. climate change). For the illustration, we first assume a 0.5%/year decrease in water inflow over a period of 40 years. This creates an aggregate trend of −20% over the entire 40-year period. Subsequent results consider a range of trends from −20% to +20%.

Second, we explore water supply reliability in the presence of a multidecadal climate signal, such as the Pacific Decadal Oscillation discussed in Chapter 3. We simulate the multidecadal variability by introducing an autocorrelation component into the 40-year time series of seasonal inflows. For this first illustration, we use a lag 1 autocorrelation coefficient of 0.6 (i.e. constraining inflow values for year t to be roughly correlated with the value for year $t–1$ with a coefficient of $r = 0.6$). This results in the time series of inflows having substantial spectral power at decadal-to-multidecadal timescales. This lag 1 correlation magnitude of 0.6 is for illustrative purposes only and will differ based on the actual system. The higher the value, the larger the fraction of variance in the multidecadal timescales. Note that systems that are only weakly impacted by multidecadal climate modes like the Pacific Decadal Oscillation will have lag 1 autocorrelation values that are much lower than the 0.6 value used here. Indeed, the Angat inflow series has almost zero lag-one autocorrelation. Thus, the results with the multidecadal traces are intended to illustrate the types of reservoir management challenges in regions which are impacted by multidecadal climate variations, such as the Sahel region of West Africa. It should also be noted that for a given system, other time-series representations may be more appropriate than the simple lag-one autocorrelation model that is used here.

Third, we also consider a scenario in which both the trend and the multidecadal variability are present. Effectively we are partitioning the variance into the three groups described in Figure 3.2b (trend), 3.2c (decadal variability) and 3.2d (interannual variability) and making assumptions about the magnitude of trend and magnitude of random decadal variability in the future, while for these simulations, maintaining a constant magnitude of random interannual variability (consistent with the historical period).

Figure 5.9a, b, c below displays a range of the stochastically simulated inflow traces for each of these approaches. They also provide trend lines to provide a sense of the possible trends across the simulated traces.

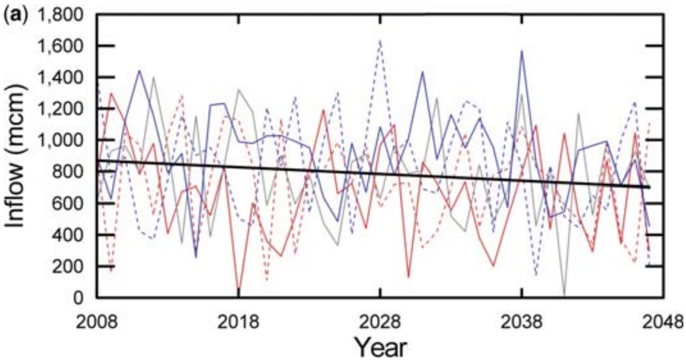

Figure 5.9(a) Projected inflow traces with a long-term trend of −20%, interannual variability consistent with the historical record, and no systematically imposed multidecadal variability.

Traces sampled from 100 simulations. Traces were ranked by their 40-year average (which varies slightly due to random sampling); traces shown are the ones ranking 10*th (red), 30th (red dash), 50th (gray), 70th (blue dash) and 90th* (blue). Black solid line is the trendline average for all inflow traces (4.2 mcm/year decrease). *Source:* Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

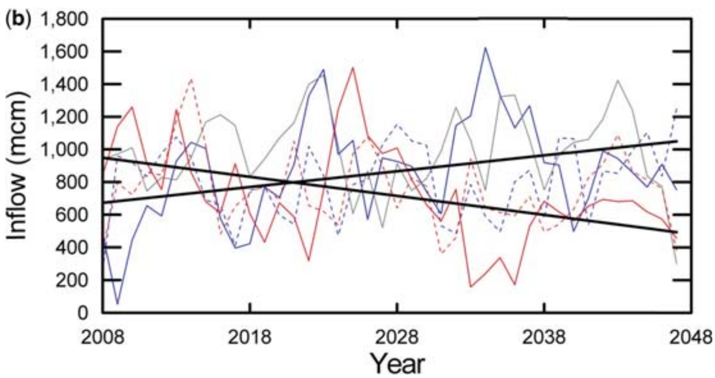

Figure 5.9(b) Projected inflow traces with no systematically imposed long-term trend, but with a randomly imposed multidecadal variability (imposed lag 1 autocorrelation, $r = 0.6$).

Traces sampled from 100 simulations. Traces were ranked according to slope of trendline (derived using ordinary least squares regression); traces shown are the ones ranking 10*th (red), 30th (red dash), 50th (gray), 70th (blue dash) and 90th* (blue). *Source:* Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

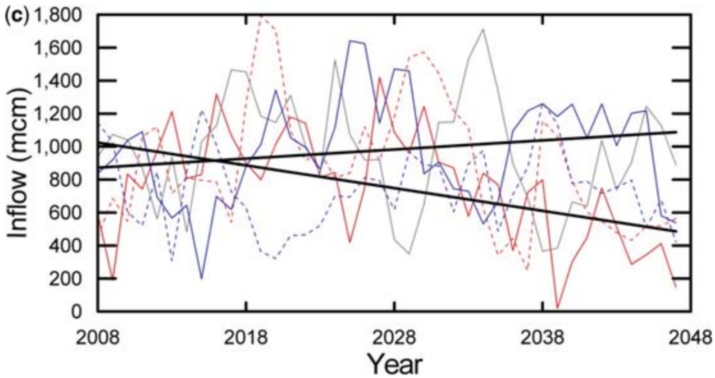

Figure 5.9(c) Projected inflow traces with a long-term trend of −20% and a randomly imposed multidecadal variability (imposed lag 1 autocorrelation, $r = 0.6$).
Traces sampled from 100 simulations. Traces were ranked according to slope of trendline (derived using ordinary least squares regression); traces shown are the ones ranking 10*th (red), 30th (red dash), 50th (gray), 70th (blue dash) and 90th* (blue). *Source:* Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

Figures 5.9a, b, c illustrate that over a 40-year timeframe, water resources managers need to be aware of the potential range of trends that can result from multidecadal variations in the climate system. Consultation with climate experts for the region of operation should inform the appropriate stochastic time-series model and magnitude of random variation to assume. In addition to guidance on the magnitude of random multidecadal fluctuations to plan for, consultation can also inform whether any tendency for increased or reduced flows is expected in coming decades (for example, see the discussion of the PDO in Chapter 3, Section 4; Prediction over longer timescales, Chapter 4, Section 2.2, and Meehl *et al*. 2009).

Table 5.2 illustrates the changes in average reservoir reliability for the different scenario types. For the simulations with systematic trend (but with no imposed multidecadal variation), Figure 5.10 shows the evolution of the average reliability across all 100 simulations for each year.

The simulated long-term trend of −20% clearly results in a significant decrease in reliability. Assessment of the system's sensitivity to climate changes in this way provides insights to vulnerability and can be an important input to risk assessment. Altering the simulation management strategies (such as allocating less water) can reveal actions that achieve satisfactory outcomes in the presence of climate change. It can therefore provide insight into which allocation strategies can be expected to be more resilient to given magnitudes of climate changes.

Inclusion of a multidecadal signal produces much less impact on the average reliability, because across the 100 simulations, phases of positive and negative inflow will on average cancel out. However, the inclusion of the multidecadal signal has other significant impacts. To illustrate one aspect of this impact that is important for water management, we have developed an indicator we call the *cumulative deficit statistic*.

Table 5.2 Sensitivity metrics for reservoir system based on simulated climate scenarios.

Inflow scenario				
Trend 2008–2047 (%)	**AR process lag 1 correlation**	**Cumulative Deficit Statistic 2038–2047 (mcm)**	**Reliability 2008–2017 (%)**	**Reliability 2038–2047 (%)**
0	0.0	59	64	65
+20	0.0	33	68	82
−20	0.0	94	65	49
+20	0.4	46	66	77
+20	0.8	64	70	79
−20	0.4	139	62	44
−20	0.8	198	65	46
0	0.4	73	64	64
0	0.8	145	64	62

Reliability estimates are based on the average of 100 simulated projections of inflow traces for each of the scenarios given by columns 1 and 2 in the table. So, for example, with a downward inflow trend of 20% and multidecadal variability imposed through an autoregressive process with lag 1 correlation of 0.8, average reliability falls from 65% in 2008–2017 to 46% in 2038–2047. The cumulative deficit statistic (defined in the text and see Figure 5.11) is calculated for the last 10 years of the simulation. It represents the maximum cumulative deficit during 2038–2047 that would be expected to be exceeded on 10% of occasions under the given inflow scenario. The results reveal the significant effect of systematic trend and multidecadal variability on the risk of a large cumulative deficit that must be planned for. Source: *Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation*.

The cumulative deficit statistic is calculated in a two-step process (see Figure 5.11). First, we calculate the maximum cumulative short-fall during the last 10 years of each simulation. We rank these short-falls (from 1 to 100) and take the 90th percentile of the ranked distribution. This indicator provides a value for the 90th percentile of the maximum shortfall volume (mcm) that accumulates over consecutive years within the last ten years of the period (2037–2047). In other words, the cumulative deficit statistic value is the maximum cumulative shortfall (over the last ten years) that would be expected to be exceeded 10% of the time. The shortfall (deficit) is the difference between the threshold level and the simulated reservoir level at the end of March. The maximum cumulative deficit is the highest cumulative shortfall attained when summing consecutive shortfall years. If the reservoir level meets or exceeds the lower rule curve at the end of March, no shortfall is experienced.

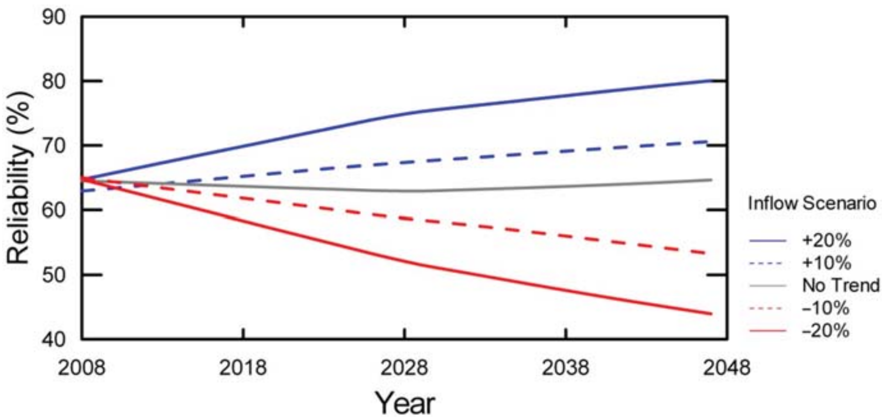

Figure 5.10 Evolution of reliability based on average of 100 simulated projections of inflow traces with a long-term inflow trend ranging from −20% to +20%, and no multidecadal variability (the type illustrated in Figure 5.9a).
The reliability is calculated as the percent of simulations in which the reservoir level is above a given threshold (lower rule curve) at the end of March each year. *Source:* Simulated traces from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

A higher cumulative deficit statistic means typically that the reservoir is facing increased severity of persistent shortfalls. This statistic provides a measure of the severity of shortfalls combined with the persistence of shortfalls, which might have serious economic consequences. For example, a farmer may be able to survive a shortfall in one year but not if there is a shortfall in two consecutive years. Table 5.2 is provided for illustrative purposes and describes the sensitivity of the water system to aspects of multidecadal variability and climate change. It includes the 10-year reliability averages as well as the cumulative deficit statistic for a range of scenarios (including positive trends to demonstrate the range of outcomes).

The results in Table 5.2 reveal the significance of the multidecadal signal. Because a certain phase of a multidecadal signal might lead to dry conditions over several years, this will increase the likelihood of consecutive shortfalls and shortfalls of greater severity. This will not usually be captured in changes in simulated average reliability, so it is important to develop metrics that capture such sensitivity in the system and provide a comprehensive risk assessment.

In the results in Table 5.2, the imposed trend may be viewed as representing potential global change (GC) effects, while the imposed AR process may be viewed as representing potential decadal-to-multidecadal variability (MDV) timescales, as generated by mechanisms internal to the climate system (such as the PDO or AMO discussed in Chapter 3, Section 4). Inspection of the cumulative deficit statistic in Table 5.2 provides an example of a relation between risk (as quantified by the statistic) and varying combinations of GC and MDV. By undertaking further simulations for multiple combination of GC and MDV (all combinations of trends covering 0%, ±5%, 10%, 15%, 20% and AR process with $r_1 = 0$, 0.2, 0.4, 0.6 and 0.8), a surface of risk can be constructed (Figure 5.12). The surface illustrates how, in this modeled system, risk varies as a function of MDV and GC, for this particular time-frame of 2038–2047.

	Year 1	Year 2	Year 3	Year 4	Year 5	Max cumulative deficit
Simulation 1	8	3	7	–3	–4	–7
Simulation 2	4	0	9	10	7	--
Simulation 3	6	9	–2	10	-1	–2
Simulation 4	–7	7	–6	–2	-8	–16
Simulation 5	–3	–5	1	–4	-1	-8
Simulation 6	2	4	10	–5	1	-5
Simulation 7	10	–2	8	2	9	-2
Simulation 8	4	5	7	3	6	--
Simulation 9	6	10	–1	6	–4	–4
Simulation 10	–4	2	3	4	6	–4

Figure 5.11 Calculating the cumulative deficit statistic.
This table demonstrates how the cumulative deficit statistic is calculated. The "Max cumulative deficit" column shows the maximum sum across consecutive deficit years for each simulation. The light blue cells indicate years with deficits, while the dark blue cells show the year(s) that make up the maximum cumulative deficit for each simulation. For example, while there are two separate 2-year consecutive deficit years for Simulation 5, the cumulative deficit in Years 1 and 2 is greater than in Years 4 and 5. The max cumulative deficit for Simulation 4 is highlighted because this represents the 90*th* percentile (the deficit higher than 9 of the 10 simulations).

It can be envisioned how the surface would look different depending on the choice of lead-time into the future (here 2038–2047) and averaging window (here 10 years), since the relative variance of GC and MDV will alter, with GC generally having a stronger more systematic signal for longer time-frames and averaging windows. In such cases, the gradient in Figure 5.12 would be amplified on the y-axis, and reduced on the x-axis (less sensitivity to MDV). For given assumptions about GC and MDV, the framework here is well-suited to explore how such surfaces of risk are modified, both with reservoir system changes and as the time-frame of concern changes. Furthermore, specific projections of GC and MDV could be mapped to such surfaces producing informed estimates of future risk, within a context of the expanded GC and MDV outcomes that are contained across the complete surface.

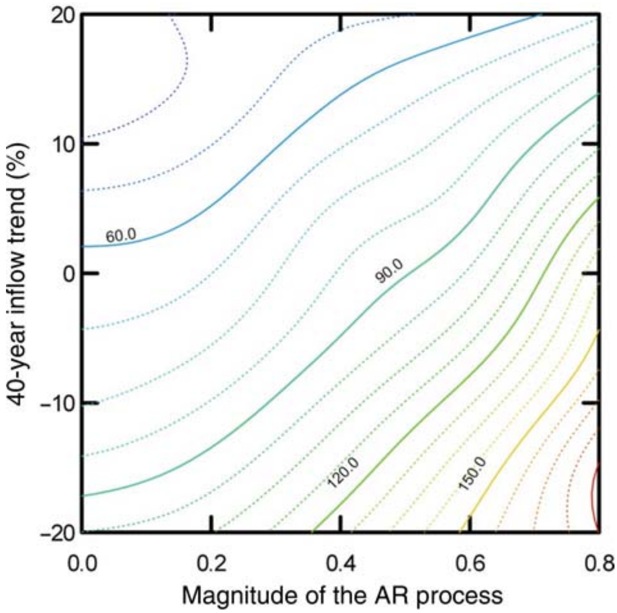

Figure 5.12 Variation of the cumulative deficit statistic (in mcm) for 2038–2047 across different inflow scenario combinations (40-year trends, given on the y-axis; and random multidecadal variability imposed as an AR process, with lag 1 autocorrelation given on the x-axis). For the given combination of AR process and trend, there is a 10% risk of a cumulative water deficit (during 2038–2047) of at least the value shown on the contour map

Step 2: Make probabilistic water supply projections incorporating climate information

Taken together, the results in the previous section demonstrate that shortfalls are a key hazard for the system and that the system is quite sensitive to hydroclimatic variability and change across multiple time scales. It is, thus, very important to take advantage of climate information and forecasting techniques to make climate projections and determine the likelihood of possible future scenarios.

For example, we could apply the seasonal forecast techniques described in Chapter 4 and Exercise 2 to develop an ENSO-based probabilistic forecast. This information would narrow the range of probable inflow levels and inform our expectations for reservoir reliability in the coming months. Additionally, Chapter 4 provides a general sense of how to construct possible future scenarios given indicators of multidecadal signals and possible long-term climate change.

It is important to remember that projections into the future will have great uncertainty, even with today's most powerful science and tools. Both the significant variability in the simulated inflow traces and the probability distribution within various scenarios (as shown in the ENSO-based forecast distributions in Figure 5.7) suggest the wide range of possibilities. Figure 5.13(a) illustrates this concept by presenting three simulated PDFs created using the SST-based inflow forecast model. These are based on historical SST conditions for three contrasting years and they demonstrate the wide range of projected mean inflows. Figure 5.13(b) then demonstrates probabilistic forecasts for each year of the 40-year period.

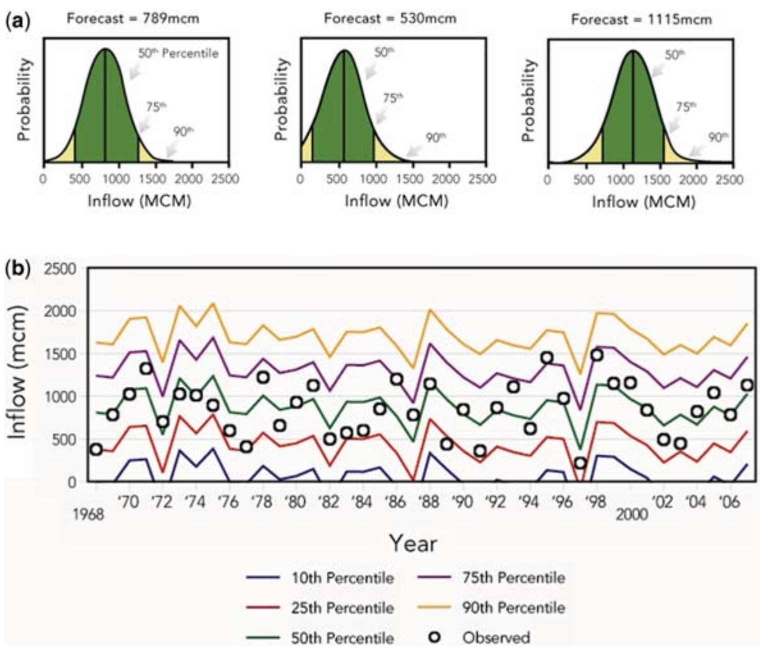

Figure 5.13 Seasonal inflow projections based on an SST-based forecast model simulated using data from the Angat Reservoir, Philippines.

Panel (a) provides the probability density function (PDF) for the years 1968, 1972 and 1998 and shows selected percentile inflow values (highlighted by the vertical lines) based on the forecasted mean and standard deviation. Panel (b) provides a time series of probabilistic inflow forecast for each year over the period 1968–2007. The 10*th, 25th, 50th, 75th and 90th* percentile forecast inflow values are shown along with the observed inflow for each year. The modeled inflow is constrained to not drop below 0 mcm. *Source:* Simulated data from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

As Figure 5.13 reveals, the forecast model, while not perfect, is able to provide a quantifiable estimate of most likely inflows that generally captures observed values. The probabilistic forecasts thus achieve the goal of effectively applying relevant climate information to help narrow the range of possible scenarios.

Step 3: Determine a portfolio of options to manage hydroclimatic risks

A number of options exist to help address the impact of shortfalls on this system. At the planning level, water managers can consider improving the water supply system (e.g. reducing leaks) and developing additional infrastructure, such as connections to other reservoirs or water sources. Such solutions may require significant investment of financial and human resources. Policy options, such as discouraging water use through regulation, may be less expensive but may also be politically challenging.

When making the choices between such options, it is important to be aware of the likelihood of future climate scenarios that would result in decreased reliability. This information can help inform an assessment of possible trade-offs that might be necessary. Of course, the uncertainty of the projections must also be considered. This will likely encourage flexible approaches that can respond to a possible decrease in reliability without causing difficulties if, for example, shortfalls do not occur, for whatever reason. In one example, the forecast of an increased likelihood of continued multi-year drought in Ceará, Brazil in 1997 led local officials to prioritize previously identified infrastructure maintenance and construction needs to increase resilience of the water supply system (Lemos *et al.* 2002). The forecast did not result in entirely new policy, rather it shifted priorities for investments that had already been planned.

Even with the best forecast, many outcome are possible, even if some are very unlikely. Thus, even with a favorable forecast, shortfalls may still occur and this must be considered. One way of addressing these possible low probability occurrences is to introduce a mechanism for financially compensating lower priority users that experience a reduction in allocated water. While this method of essentially substituting money for water might not always be effective, there is emerging theoretical evidence that such mechanisms could offer significant benefits to users (see Example 5.2).

Figure 5.14 illustrates the possible financial benefit based on simulations for the shared agriculture-urban system in Metro Manila, Philippines. The figure shows the costs to the urban sector of water supply when using contracts alone (“Contract” time series) or contracts along with insurance (“Insured” time series). The figure also demonstrates the simulated agriculture losses when no contracts are used (“Current Ag Loss” time serried). As Brown and Carriquiry (2007) note, “hydrologic variability has been transformed into financial variability”. The model uses an in-season price of water that is approximately double the preseason water price using the option contract, meaning that it is much more costly to purchase additional water when facing scarcity during the season. The results shown reveal that the insurance mechanism smoothes the highly variable costs of supplying water using the contract arrangement.

Example 5.2: Managing risks through financial mechanisms

Brown and Carriquiry (2007) undertake a simulation to demonstrate the potential for a combined option contract – reservoir index insurance system to effectively smooth water supply costs of hydroclimatic variability for both agricultural and municipal (urban) users (see also Chapter 6). If water scarcity is expected to occur, a bulk water option contract allows the urban water supplier to take some portion of the agricultural water allocation in exchange for previously agreed financial compensation. To help cover the urban supplier's compensation costs, index insurance can be developed. The index insurance is triggered based on reservoir level and can be designed to cover the costs necessary to exercise the option.

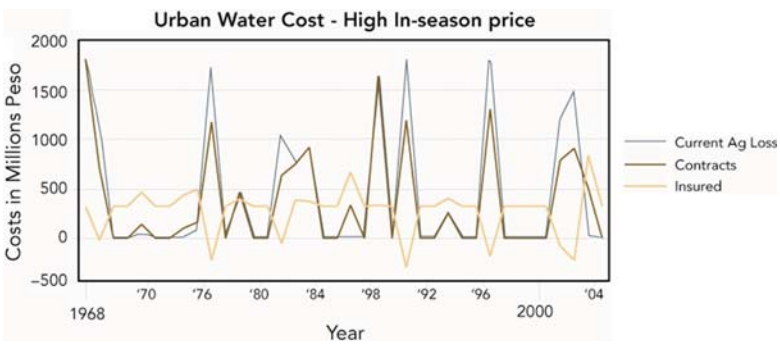

Figure 5.14 Costs to urban water agency with option contracts in place, considering outcome with and without insurance.
This figure uses an in-season water price approximately double the pre-season price. Insurance payouts to the urban supplier exceed total costs, resulting in negative costs in years when options are exercised correctly. Simulated agricultural losses without contracts in place are also shown. In the four years in which the urban sector would exercise options and the insurance does not payout, the total costs are small. Overall, the insurance effectively smoothes the costs of supply under the contract system. In seven of the years, the insurance payout exceeds the cost faced by the urban sector for purchasing water. This is due to the design of the insurance, which was formulated to cover the maximum costs. Maximum costs only occur when preseason options are not exercised. Therefore when options are correctly exercised, the payout to the insurance holder exceeds the costs, which is the case in each of these years. This excess payout could be eliminated by decreasing the insurance coverage, resulting in lower premiums. *Source:* Adapted from Brown and Carriquiry (2007).

Sensitivity to hydroclimatic changes can also be addressed at the operational level. Decision support tools that integrate climate information, particularly at the seasonal scale, may be able to help water managers improve allocation decisions with a better understanding of expected reliability. Chapter 6 explores techniques for designing, supporting, and evaluating alternate reservoir allocation strategies based on climate information, as well as other ways of incorporating climate information into operations planning for water supply systems.

CONCLUDING REMARKS

The 3-step climate risk management approach outlined in this chapter is not the only method for managing hydroclimatic risks and opportunities. However, in order for any approach to be successful, all of the key concepts captured in these three steps are necessary. It is critical to assess the historical hydroclimatic risk based on both hazard occurrences and their consequences. Such an assessment requires a dialogue with relevant stakeholders in addition to climate professionals who can locate and interpret data. Managing risks must also involve engaging with colleagues in climate science to develop a shared understanding of how hydroclimatic risk is likely to change in the future (across all time scales). Ultimately, this knowledge must be translated into anticipatory action through some balance of operational decision making and planning. Chapter 6 explores some of the practical details involved in implementing and improving the final step.

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Chapter 6

Techniques for using climate information in planning and operations

INTRODUCTION

The climate risk management framework described in Chapter 5 identifies the steps for characterizing the hydroclimatic risks facing a water supply system and determining how climate information can reduce the uncertainty contributing to these risks. This facilitates anticipatory actions in order to manage hydroclimatic risks and mitigate the possible negative consequences of climate variability. There are a variety of techniques for taking advantage of climate information in developing these anticipatory actions. This chapter outlines some of the innovations in this field and demonstrates some key techniques. After focusing exclusively on integrating climate information in reservoir operations and management in the first part of the chapter, the second part considers other techniques with broader applications.

Section 1: Reservoir management

We focus our discussion in this section on using climate information in multipurpose reservoir operations balancing the water supply needs of multiple user groups (e.g. municipal, industrial, agricultural and hydropower users). By addressing these more complex situations requiring balancing multiple objectives, the principles and techniques described below can easily be applied to reservoirs with single or many users. The discussion is focused on operating decisions made on a monthly or seasonal basis (as opposed to hourly or daily operations, such as flood control). While we primarily discuss single reservoirs, all the concepts can be applied to more complex multi-reservoir systems. The section begins with a discussion of integrating climate information in reservoir rule curves. This also provides a basis for understanding how climate information can be used in broader decision support systems. We then examine the importance of evaluating outcomes from these techniques and explore this in the context of a stylized example.

Section 1.1: Storage rule curves

The operation of many reservoirs is guided by storage *rule curves,* which specify target storage levels for different times of the year. The goal is to provide sufficient water during dryer periods and provide reservoir space for refill during wetter periods by maintaining the target storage elevations. Historically, rule curves have been developed through trial-and-error simulation of the reservoir system (accounting for inflows, releases, evaporative losses, etc.). However, water managers can also use optimization methods similar to those described in section 2.1 of Chapter 2. Most methods determine the storage level requirements based on a targeted reservoir reliability. Figure 6.1 shows an example of a storage rule curve, along with the average monthly inflows to the reservoir. As shown in this figure, the reservoir is drawn down during the dry season and is expected to refill during the wet season each year.

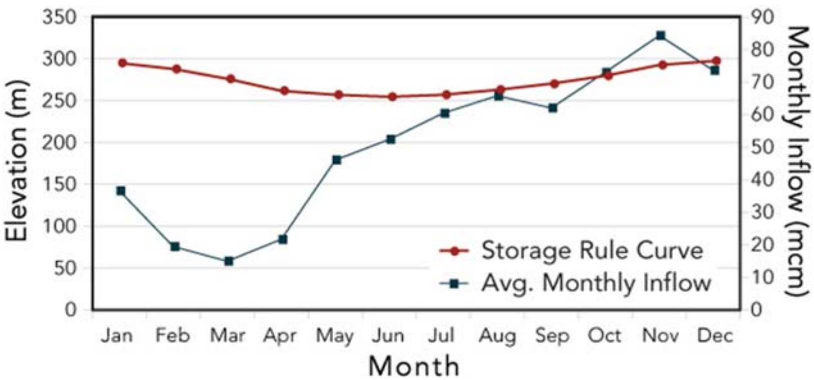

Figure 6.1 Storage rule curve and average monthly inflows to Lake Madden, Panama. Reservoir level is drawn down during dry season with the expectation that higher flows in the wet season will refill it each year. *Source:* Adapted from inflow data, USACE (2000).

If storage levels drop (or are projected to drop) below the rule curve, water releases may be curtailed. The amount of the curtailment or hedging, and the *trigger* levels for initiating various levels of curtailment, are important components of a reservoir operating policy. A storage rule curve alone does not provide a complete set of rules for operating a reservoir because there is no specification of how much releases can (or should) be increased or decreased if the storage deviates from the target levels. Thus, some combination of a storage rule curve and a hedging rule with specified rationing factors is typically applied in practice. For example, if the storage drops below a given rule curve, releases to meet various user demands are not completely shut off, but rather are curtailed by some amount in accordance with the storage deficit.

Even though conditions such as initial storage level, inflows and user demands can vary significantly, reservoir operators generally use static rule curves that remain the same from year to year. Since rule curves are generally developed to avoid shortfalls during a *worst case scenario*, water managers often feel comfortable relying on them to support decisions. However, the worst case scenario is drawn from historical experiences and likely does not capture nonstationarity in the system. In addition, managing only to avoid a worst case scenario limits the ability to take advantage of possible opportunities from available water under conditions that prevail in most years. These concerns can be partly addressed by updating rule curves and developing multiple rule curves that take into account relevant conditions, as described in the next section.

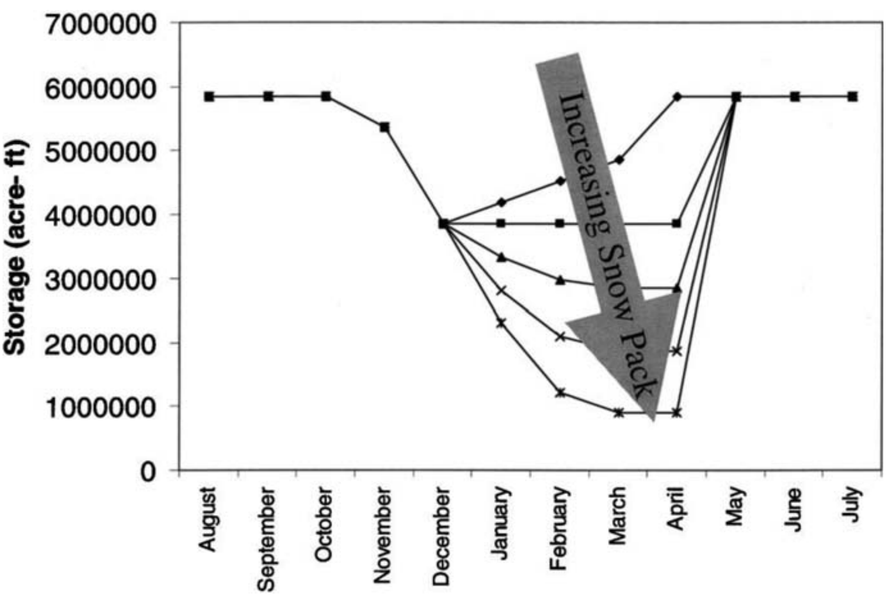

Figure 6.2 Example of a conditional (adaptive) flood storage rule curve set, based on conditions at the Libby Dam in Montana, United States.
With increasing snowpack, flows are expected to be higher, resulting in the need for increased flood control storage. The rules indicate that increased snowpack conditions up to January should lead to drawdown of the reservoir to allow for increased flows from the snowpack melt. Units are in acre-feet, where 1 acre-foot = .001233 mcm. *Source:* Hamlet *et al.* (2002).

Conditional storage rule curves

Although rule curves are generally static and based on current storage in the reservoir, they can also be derived from other quantities or indicators. For example, sets of rule curves may be developed to account for antecedent conditions (e.g. precipitation in the last 15 days), or projected inflows to the reservoir. The water manager can use multiple rule curves: one for dry antecedent conditions (based on historical record), another for wet conditions, and a final one for average conditions. Figure 6.2 shows an example of a flood storage rule curve set with rule curves conditioned on snowpack-based runoff forecasts. Hydrologists have integrated such snowpack run-off considerations into operation rules for decades (Beard, 1963). These are sometimes referred to as conditional or adaptive rule curves.

In Figure 6.2, rule-based release decisions starting in January rely on antecedent conditions affecting snowpack. If antecedent conditions up to January had resulted in relatively high snowpack, the water manager can use this rule curve to suggest that reservoir levels can be drawn down to allow for sufficient flood control storage in April. While the goal in this case is to reserve adequate flood control storage, a similar approach could be used for water supply. In the case of multi-reservoir systems, the combined storage of the reservoirs may be considered.

Water resources managers can apply the basic concept of conditional or adaptive storage rule curves to information based on seasonal climate forecasts. Assume we

EXAMPLE 6.1: Developing streamflow forecasts for use in water resources management that integrate interannual climate variability (ENSO), decadal climate variability (PDO), and snowpack

The Climate Impacts Group at the University of Washington has been working on streamflow forecasts for rivers in the Pacific Northwest region of the United States for over a decade. They have identified three types of rivers in the region: snowmelt dominated, rain dominated, and mixed (transient snow). The snowmelt dominated rivers have the most significant seasonal hydrologic response, indicating that the streamflow is most variable and dependent on seasonal conditions. Additionally, the team found that both ENSO conditions and the phase of the Pacific Decadal Oscillation (PDO) impact streamflow for the 26 rivers they studied in the region (Figures 6.3 and 6.4), with the greatest effect on snowmelt dominated rivers. (For a further example of the interaction of snowmelt, ENSO and PDO, see Hidalgo & Dracup (2003), which focuses on the Upper Colorado River Basin in the United States).

Based on these findings, members of the team developed hydrological forecast models for specific rivers based partly on initial snow conditions, and integrating the ENSO climate signal and the existing phase of the PDO. For the Columbia River, the forecasts provide much greater skill and increase the lead-time by about six months compared to existing statistical forecasts based on observations of snowpack (Hamlet & Lettenmaier, 1999).

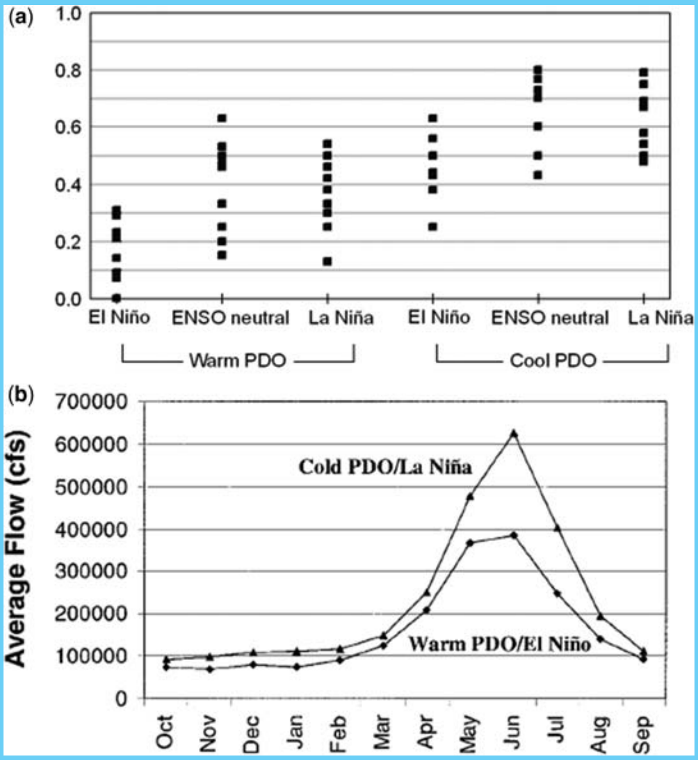

Figure 6.3 Probability of flooding and average historical inflow for the Columbia River based on ENSO and PDO.

Panel (a) shows the probability of flooding for snowmelt dominated rivers based on ENSO/PDO phase. A value of .8 is equal to an 80% probability of flooding during spring and summer periods. La Niña conditions and the cool PDO phase increase flooding probability relative to opposite phases. Panel (b) shows the average historical inflow for Columbia River based on ENSO and PDO phase. Units are in cubic feet per second (cfs), where 1 cfs = .0283 cubic meters per second (cms). *Source:* (a) Climate Impacts Group, Center for Science in the Earth System at University of Washington. Accessed at http://cses.washington.edu/cig/res/ hwr/deadendfigure4.shtml (b) Hamlet and Lettenmaier (1999).

The Climate Impacts Group has continued to develop experimental, real-time twelve month forecasts for hydrologic conditions in the Western United States (see http://cses.washington.edu/cig/fpt/waterfc/weststreamflowfc.shtml). They also share these forecasts and other information regarding ENSO conditions, the PDO status and streamflow forecasts via their Climate Outlook website and workshops with utilities, water managers, forecasting agencies and the general public in the region (see http://cses.washington.edu/cig/fpt/cloutlook.shtml).

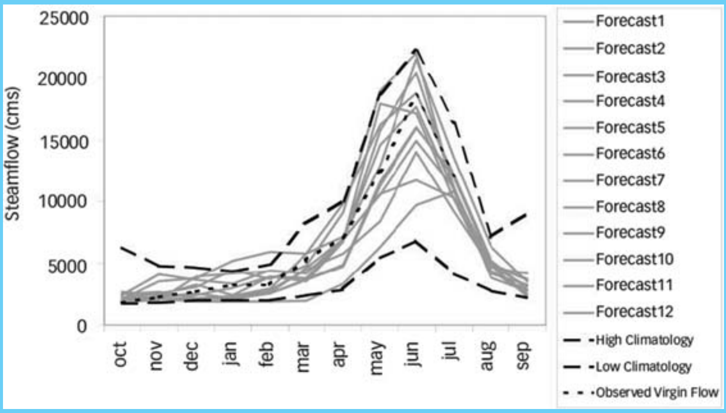

Figure 6.4 Streamflow forecast for the Columbia River for 1999.
This graph is based on resampling from the historical record using analog conditions to predicted ENSO and PDO phase, as well as snowpack conditions produced. Produced in June and offering a six month lead-time. *Source:* Hamlet and Lettenmaier (2000).

have an initial static rule curve that was developed based on the climatological record, with the goal of ensuring reservoir refill with a high degree of reliability. We can then create a conditional rule curve that can be adjusted up or down to maintain the same level of reliability based on the forecasted reservoir inflows. For example, if the forecast indicates that wet season inflows will likely be higher than the climatological average, the reservoir may be drawn down further during the dry season to maximize beneficial uses. However, if the forecast indicates inflows will likely be less than average, the reservoir may be kept higher to ensure refill. Figure 6.5 shows an example for the Madden Reservoir in Panama, with separate rule curves based on the observed ENSO state.

This is a very simple example, and in practice a more detailed study would likely be needed to account for the consequences of shortfalls in water allocations and carry-over storage, the reliability of the forecasts, and the ability to update forecasts or mitigate consequences over time. The simulation and optimization methods discussed in Chapter 2 and Appendix 1 may prove useful in such a study. Taken together, these methods demonstrate how seasonal climate forecasts might be used to guide decisions so that anticipatory actions can be taken to improve management outcomes based on the available climate information. The following section explores how such conditional rule curves and other climate forecast-based tools can support water allocation.

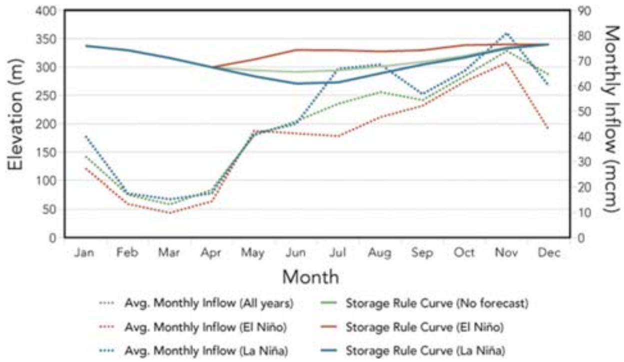

Figure 6.5 Storage rule curves and average monthly inflows to Lake Madden, Panama, for El Niño events, La Niño events and across all years.

Rule curves are adjusted in May to reflect the reservoir drawdown suggested based on expected inflows the rest of the year to ensure approximately the same reliability of refill by the end of the year. Since La Niño events lead to higher average inflows for this system, the rule curve decreases to recommend drawdown and allow for increased inflows to refill the reservoir. El Niño events lead to drier than average conditions and are accompanied by a higher rule curve. The model assumes perfect foresight of ENSO conditions (i.e. perfect knowledge of whether one is entering an El Niño or La Niña event). *Source:* Adapted from inflow data, USACE (2000); ENSO data accessed from NOAA Climate Prediction Center at http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ ensoyears.shtml.

Section 1.2: Integrated forecast-decision support models

In order for climate information to improve water resources management, it must somehow be integrated into decision making. One technique for achieving this is to implement a water allocation decision support model that uses climate-based forecasts as inputs. Following the discussion in Chapter 5, the basic idea is to use climate information to narrow the range of likely reservoir inflows in order to support improved water allocation decisions (i.e. avoid decisions that lead to shortfalls or fail to take advantage of available water). One way to proceed is to explore how forecasts can be integrated into existing models and approaches in a variety of ways, often using simulation, optimization or some combination of the two.

Conventional water allocation models have typically been deterministic (i.e. based on a single expected streamflow sequence), as described by Yeh (1985) and Lall and Miller (1988). More recently, water managers and researchers have started to focus on the probabilistic nature of streamflow and streamflow forecasts. These inputs are often represented in the form of *ensembles*, or sets of possible streamflow sequences representing the range of future values. As suggested in Chapter 5, it is critical to consider a range of possible scenarios informed by forecasts and associated uncertainty. Conventional water allocation models can often be adapted to utilize ensemble inflow forecasts. Below we present some examples of possible methods for achieving this for seasonal inflow forecasts.

Kracman *et al.* (2006) describes a probabilistic optimization model of the Highland Lakes system in Texas, USA. The model receives ensemble reservoir inflow forecasts and determines water management decisions that maximize the expected value of an economic objective function. In this initial study, the ensemble flow forecasts are based on climatology, with each sequence sampled from the historical record and assumed equally likely. Thus, this approach does not actually consider conditional seasonal forecasts.

However, several procedures have been developed to allow consideration of seasonal forecasts in probabilistic optimization models. One approach is to use sequences from the historical record, but adjust the conditional probability of each sequence to match the probabilistic forecast (Croley, 2000). Another approach is to sample sequences from the historical record according to the conditional probability forecast. This can be performed using a method such as the nearest-neighbor bootstrap (Lall & Sharma, 1996; Grantz *et al.* 2005), as illustrated in Figure 4.6 of Chapter 4.

EXAMPLE 6.2: Integrating climate information into decision support for agriculture

Highly variable climate and impending threats from climate change are intensifying concerns over water allocation for agricultural needs in Australia. There is a wide range of climatic phenomena affecting rainfall variability across various time scales over the continent (e.g. a phenomenon called the Madden-Julian Oscillation (MJO) at the intra-seasonal time scale, ENSO operating at seasonal to interannual time scales, and the Pacific Decadal Variability). Decisions in the agricultural sector also occur at similar time scales as these climatic patterns, including logistics and crop management within the season, crop sequencing and rotations at the interannual time scale, and crop industry investments made at a decadal scale (Meinke & Stone, 2005). The ability to forecast rainfall and climate conditions thus has significant implications for agricultural and irrigation-related decision making in Australian.

While not all of the climatic phenomena can be adequately modeled or skillfully forecasted, seasonal climate models are particularly promising for the Australian context. A variety of operational seasonal forecast approaches have been developed to serve as inputs to crop models and irrigation allocation models, including both analog statistical approaches based on historical conditions related to ENSO phases and GCM-based approaches, which appear to offer increased skill during a critical cropping period in April when ENSO conditions are a less reliable predictor (Stone & Meinke, 2005). There is increasing emphasis on building collaborative relationships between climate professionals and agricultural decision makers and institutions.

One example of an outcome from these collaborations is the development of the *WaterWorks* decision support tool that supports Australian irrigators in making long- and short-term irrigation infrastructure investment decisions at the farm level (Khan *et al.* 2009). The tool uses simulation and optimization techniques to model costs and benefits of cropping, management, investment and water allocation decisions. Climate-based seasonal water forecast models can serve as an input to predict water availability and simulate allocation, which can then be used to optimize water trading prices.

The tool has been validated and accepted by a community of irrigators and researchers in New South Wales, Australia, showing possible economic benefits (Khan *et al.* 2009). In a separate study, researchers have estimated that improved seasonal allocation forecasts could produce significant economic benefits for irrigators, particularly when water scarcity is expected to results in lower than average allocations (Mushtaq *et al.* 2009).

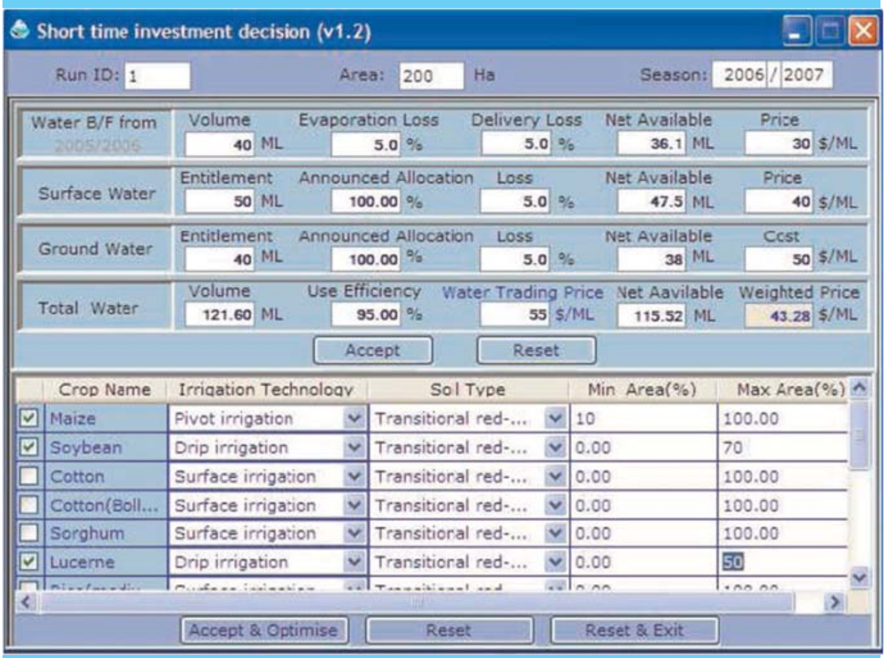

Figure 6.6 WaterWorks seasonal investment decision tool.
Climate-based seasonal forecasts can provide the input for the surface water allocation.
Source: Khan *et al.* (2009).

Sankarasubramanian *et al.* (2009) describe a simulation model of the Angat Reservoir in the Philippines, which provides water supplies to the City of Manila. The model receives probabilistic reservoir inflow forecasts for the October-February season based on a GCM model that is run with persisted SSTs (Figure 6.7). The probabilistic reservoir inflow forecasts are represented as ensembles of monthly inflows ($N = 500$), which are generated based on the conditional mean and point forecast error of the forecast model (in this case a principal components regression model). It is assumed that the monthly flows follow a multivariate normal distribution and that the month-to-month correlation of the forecasted flows is the same as climatology.

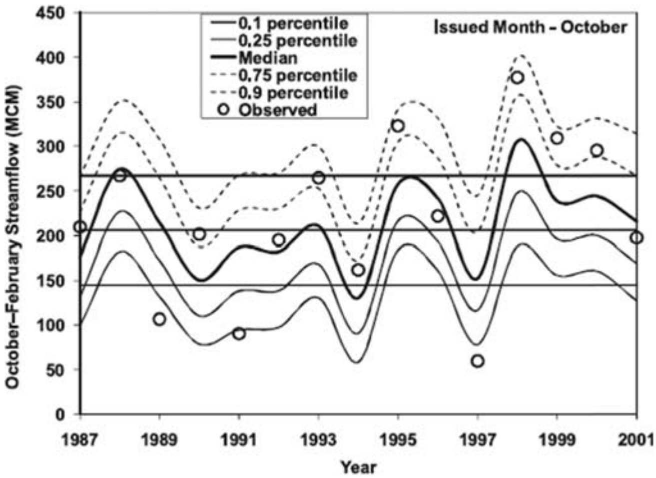

Figure 6.7 Conditional distributions of seasonal streamflow forecasts based on precipitation forecasts from a downscaled GCM using previous season SST.
The updated seasonal streamflow forecasts are issued in the beginning of October for the remaining months in the October-February season for the period 1987–2001. *Source:* Sankarasubramanian *et al.* (2009).

The reservoir model uses the probabilistic inflow forecasts to determine the water allocation for municipal, agricultural and hydropower uses. Sankarasubramanian *et al.* (2009) modify the conventional allocation model to accept forecast ensembles in the form of climate-conditioned streamflow distributions. Water allocation is simulated by following a storage rule curve, requiring a specified reliability of being above the curve at the end of the season, and assuming a simple priority-based rule which allocates water first to municipal users, then agricultural, and finally hydropower.

Sankarasubramanian *et al.* (2009) present their allocation model as a "dynamic allocation framework". A slightly different approach builds off the concept of conditional rule curves described above. Brown *et al.* (2009) run simulations of the same system, the Angat Reservoir, that utilize rule curves that are updated each year based on climate-based inflow forecasts. Such "dynamic rule curves" are an emerging technique for integrating inflow forecasts directly into storage rule curves, which can then be imbedded in a full decision support system, in order to support allocation decision making.

Exercise 4: Integrating seasonal forecast information into reliability analysis for a multipurpose reservoir

Exercise 4 builds off previous exercises to demonstrate how the probabilistic seasonal inflow forecast developed in Exercise 3 can be applied to historical conditions and used to determine expected reliability for a multipurpose reservoir. Here you will be able to construct a seasonal inflow forecast, use it as an input in a stylized decision support model, and observe how changes in water allocation can affect the expected reliability. The exercise also provides the observed inflow from the historical record as a point of comparison for the forecasted inflow.

Section 1.3: Evaluation of outcomes from using climate-based forecasts

When developing and implementing decision support tools that rely on climate forecasts, it is essential to evaluate their possible benefits and assess possible disadvantages. Chapter 4 describes techniques for validating the climate forecasts and determining their skill. Water resources managers can work with climate scientists to develop "hindcasts", which are simulated forecasts for some period in the past that can be compared to actual observed values (e.g. for inflow) to help evaluate skill. The specific hindcast procedure depends on the method being used to generate the forecasts. For example, while you might test a dynamical forecast model by comparing observed values to those predicted from initializing the model with historical conditions, you could evaluate a statistical forecast model using cross-validation techniques similar to those explored in Chapter 4 and Exercise 2. A set of hindcasts can also serve as an input to a water allocation model (e.g. storage rule curve or decision support system) to determine whether or not using the hindcasts would have led to increased benefits.

To demonstrate some more detailed methods for evaluating benefits, we provide an assessment of a stylized decision support tool based on a combination of historical and synthetic data for the multipurpose Angat Reservoir in the Philippines. For this example, we simulate a simple seasonal climate forecast based on a linear regression between historical SST anomalies (using the Nino3.4 index) and Angat reservoir inflows (see Chapter 4 and Exercise 2 for details on this approach). We then apply the model with historical values of SST anomalies to create a series of forecasts for the system.

We also developed a stylized decision support tool that determines an allocation scheme between municipal, agriculture and hydropower users. The stylized decision support tool in Exercise 4 allows exploration of expected reliability for alternate water allocation choices. The expected reliability for each choice of allocation is based on the available seasonal forecast of inflow. This is valuable to see the implications of using the forecast in specific years. However, this does not provide the user with an estimate of expected long-term benefits of adopting water allocations that are responsive to the seasonal inflow forecasts. We can add a further sophistication to the decision support tool to enable such estimates of long-term benefit. In doing so, allocations can be determined to achieve a desired reliability. For the illustrative results presented in the remainder of this section, the desired reliability is set to 90%. This then allows comparisons of the statistics of reservoir performance (long-term average, number of failures, etc.). Comparisons may be made for a system that is optimized for the (climatological) inflows of the last 30 years versus a system that is optimized using a seasonal forecast of inflow in each year. We can also use this tool to compare the performance of the reservoir in the presence of imposed trends in the inflows, and explore which strategies are most robust – a valuable insight in the presence of the global environmental changes that are underway.

In estimating the water allocation that corresponds to 90% reliability, the standard error on the seasonal forecast plays a critical role. The standard error determines the distribution of inflows, which is needed to find the allocation that corresponds to a 90% probability of successful delivery. If the standard error is underestimated, forecasts will be too confident, and allocations will respond too strongly to the forecast. Therefore, we make a conservative estimate of the standard error as the standard deviation of forecast errors, after the application of a cross-validation procedure (see Chapter 4, Section 2.1, evaluation of forecast model skill).

The stylized reservoir model assumes that the allocation schemes are determined at the beginning of the season and are not updated as the season progresses. Although this is not a fully realistic assumption, it allows us to simplify the model while still demonstrating possible outcomes from using climate-based forecasts. Additionally, the evaluation only considers the hydrologic impact on the reservoir and does not translate this into economic losses or benefits. A cost function could be applied to the findings to estimate the economic impacts. While this is a stylized example, the methods and concepts can easily be applied to many other contexts and systems.

General results

Table 6.1 and Figure 6.8 reveal the modeled frequency and average value of surpluses, shortfalls and spills. For this example, a surplus occurs whenever the amount of water allocated is less than the amount available based on observed inflows. This can be considered a lost opportunity because more water could have been allocated to water users. A spill occurs whenever the surplus is so large that it exceeds the reservoir storage capacity and must be released (spilled). Finally, a shortfall occurs whenever the amount of water allocated due to the forecast exceeds the amount of water available based on observed inflows. For this example, it is assumed that there is always sufficient water in the reservoir to meet total allocations. However, the reservoir may need to be drawn down below the lower threshold to meet the demand, resulting in a shortfall. Thus, a shortfall is the difference between the end-of-season volume and the lower threshold level when this value is negative.

Table 6.1 Differences between end-of-season reservoir volume and desired minimum threshold (based on the lower rule curve).

	Climatology	Forecast
Average difference (mcm)	478	421
Average surplus (mcm)	564	478
Surplus frequency	35	36
Max surplus (mcm)	1380	1103
Average spill volume (mcm)	254	215
Spill frequency	13	9
Max spill volume (mcm)	718	440
Average shortfall volume (mcm)	−122	−99
Shortfall frequency	5	4
Max shortfall volume (mcm)	−281	−194

The data here take into account observed inflow from the historical record and total amount allocated to municipal and agriculture users (i.e. difference = end-of-season volume minus threshold level). Period of analysis is 1968–2007. For "Climatology", amount allocated is based on 3-month inflow projection using the distribution from historical climatology. For "Forecast", allocated amount is based on a distribution from an SST-based inflow forecast. Positive difference values (surplus) indicate amount of water in excess of lower threshold volume, while negative difference values (shortfall) indicate amount of water less than lower threshold volume. Spill volume indicates amount of water in excess of upper threshold volume that must be release to protect the reservoir. Source: *Simulated data from IRI; Angat inflow and storage level data from Philippines National Power Corporation.*

The results above illustrate that the SST-based forecast offers benefits over using climatology to make allocation decisions. While there are certain years in which using the SST-based forecast inflows does not result in an improved outcome (i.e. results in an even worse outcome than using climatology), using the forecast inflows reduces both the average and maximum shortfalls, surpluses and spills.

These represent lost opportunities to the system through either lost revenues or costs due to shortfalls.

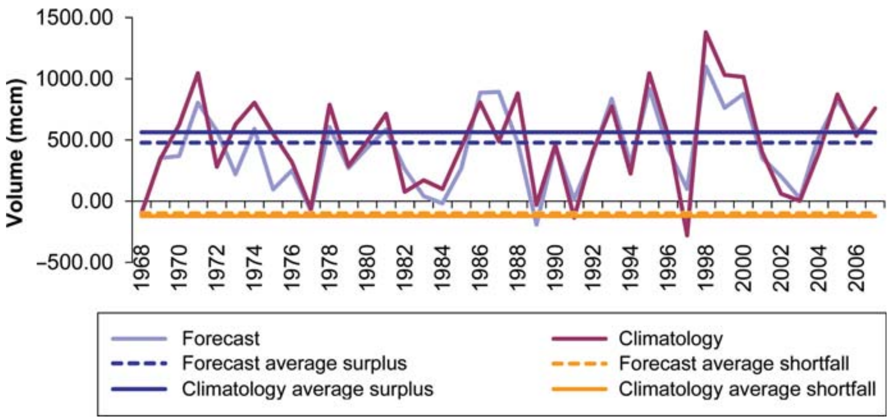

Figure 6.8 Time series of differences between end-of-season reservoir volume and desired minimum threshold (based on the lower rule curve).
Please see Table 6.1 for more details. Source: Simulated data from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

Another way of considering the benefit is to compare the end-of-season reservoir level (relative to the critical threshold) using climatological information (478.0 mcm) and climate forecast information (421.7 mcm) (see Table 6.1). This indicates that the reservoir is, on average, drawn down an extra 56.3 mcm each year when using the climate forecasts, while nonetheless maintaining the same reliability. The extra draw-down represents the additional water that it is possible to allocate to users, which over the 40-year simulation period, amounts to 56.3 * 40 = 2252 mcm.

Results by sector

We can also separate the analysis by sector to understand how managing with the SST-based inflow forecast might affect the agriculture, municipal and hydropower users. Table 6.2 and Figure 6.9 demonstrate the results of this analysis. For these results we use the terms *lost opportunity* and *shortfall* to more appropriately reflect how the conditions are experienced by each sector. As described above, a lost opportunity occurs due to a surplus of available water. A shortfall, on the other hand, means that meeting the requested allocation required reducing the reservoir storage below the lower threshold level. Since this is a priority system with municipal users having highest priority, it is assumed that the shortfall losses will be borne fully by agriculture (in the form of future reductions to address the reservoir deficit). In these results, each occurrence of a spill is considered as a lost opportunity for hydropower, since the allocation rules for the model indicate that water above a given threshold (the spill level) can be released for hydropower generation.

Table 6.2 Differences between amount of water allocated to different users and amount of water actually available above lower threshold based on historical observed inflows.

	Climatology	Forecast
Lost opportunity frequency for agriculture	35	33
Average lost opportunity for agriculture (mcm)	428	383
Shortfall frequency for agriculture	5	5
Average shortfall for agriculture (mcm)	−113	−50
Lost opportunity frequency for municipal	0	3
Average lost opportunity for municipal (mcm)	0	111
Lost opportunity frequency for hydropower	9	5
Average lost opportunity for hydropower (mcm)	186	124

The period of analysis is 1968–2007. For "Climatology", the amount allocated is based on a 3-month inflow projection using the distribution from historical climatology. For "Forecast", the allocated amount is based on a distribution from an SST-based inflow forecast. Positive values (lost opportunity) indicate the amount of water in excess of lower threshold volume that could have been allocated to the user but was not. Negative values (shortfall) indicate the amount of water less than the lower threshold (i.e. the amount that should not have been allocated and resulted in a shortfall). Since hydropower can only operate if other users receive their requested allocation, shortfalls do not occur for hydropower generation. Source: *Simulated data from IRI; Angat inflow and storage level data from Philippines National Power Corporation*.

The results illustrated above reveal how the benefits of using a seasonal forecast rather than climatology are distributed across sectors. With the exception of lost opportunities for municipal users, the forecast consistently reduces the frequency and magnitude of negative outcomes across sectors. A lost opportunity for municipal can occur in years forecast to have very low inflows, such that overall allocation is made below the fixed municipal demand, yet the actual outcome is for inflow that is greater than the amount allocated. A lost opportunity for municipal users could cause significant policy difficulties and would cause significant difficulties and would need to be addressed before implementing an actual seasonal forecast model. In addition to illustrating possible benefits, performing evaluations such as this one are also helpful for identifying these kinds of concerns.

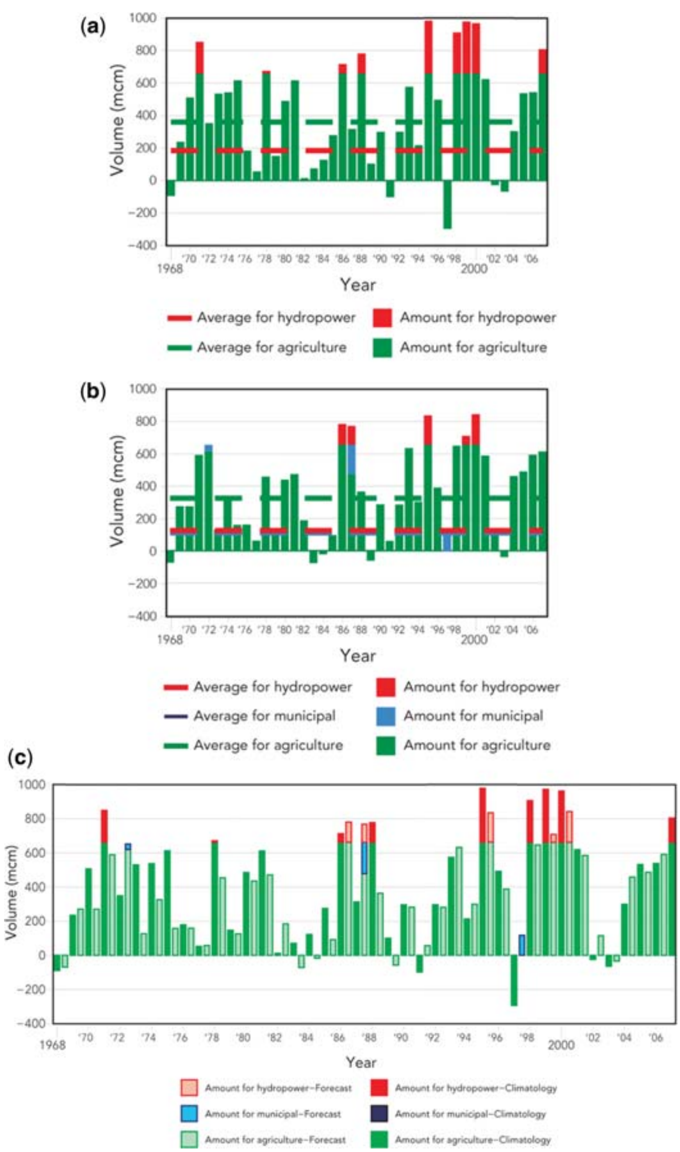

Figure 6.9 Lost opportunities and shortfalls by sector (a) based on climatology, (b) based on forecast, (c) contrasting climatology with forecast.

This is a time series of differences between the amount of water allocated to different users and the amount of water actually available above the lower threshold based on historical observed inflows from 1968–2007.

The averages shown in Panels (a) and (b) are calculated across all years and include both shortfalls and surpluses. *Source:* Simulated data from IRI; Angat inflow and storage level data from Philippines National Power Corporation.

Results with consideration of a long-term trend

We are also able to use the stylized decision support model to assess how different year-on-year management strategies alter reservoir performance in the presence of long-term trends. One management strategy that we explore is the use of the seasonal forecast (as discussed above). Now the question is the extent to which benefits from seasonal forecasts are altered by the presence of a trend, as well as the extent to which using seasonal forecasts may damp system sensitivity to climate trends. Actions that reduce sensitivity to climate are recognized as a potential component of adaptation (Mastrandrea *et al.* 2010). By having in place systems that are flexible and able to respond to real-time monitoring over weeks to months, and/or short-term seasonal forecasts, society can take on actions that, over time, are better able to cope with the new emerging climate patterns. While such enhanced management of climate variability is now widely acknowledged to be a contributor to adaptation (e.g. UNDP 2002; Meinke & Stone 2005; Klopper *et al.* 2006; Ziervogel *et al.* 2010), the extent of the contribution remains to be proven (Someshwar 2008). There are well-documented constraints to establishing flexible risk management systems for climate variability, including in the water sector (Lemos *et al.* 2002; Rayner *et al.* 2005), but also examples of progress (Pagano & Garen 2006; Feldman & Ingram 2009).

A further source of information that may be drawn upon to adjust management strategy each year is updates of the best estimate of the low-frequency climate state (i.e. an attempt to track any emerging trends and use this to estimate the expected climate for the coming year) (e.g. Livezey *et al.* 2007; Arguez & Vose 2011; and application example discussed in Siebert & Ward 2011). We illustrate incorporation of both seasonal predictions and updated climate normals, as options to potentially increase resilience in the presence of climate change.

Since this is a more complex system to construct and envision, we illustrate reservoir performance for one realization of interannual variability over the 2008–2047, and for two climate scenarios: no trend and a 20% downward trend. One approach to managing the reservoir is to make the same allocation each year, targeting 90% reliability, based on the historical climatology information (1968–2007). This can be termed static allocation (SA), since allocation is fixed to be the same each year. When management of the reservoir allows allocation to change each year based on available climate information, this can be termed dynamic allocation (DA); this is an example of dynamic management. The dynamic approach may contribute to making the reservoir more robust in the presence of climate variability and change.

To generate inflow forecast-observed pairs for 2008–2047, the forecast-observed pairs for 1968–2007 are randomly rearranged*. Therefore, there is no change in the

*For the illustration here, we assume no change in seasonal forecast skill due to global change processes. Generally, Greenhouse Gas forcing is considered to likely have most impact on the pattern of seasonal prediction skill in mid-latitudes (e.g. Sterl *et al.* 2007; Meehl *et al.* 2006) with many of the teleconnections that give rise to seasonal prediction skill in the tropics expected to remain relatively robust.

correlation skill of the forecasts, which is the same as for 1968–2007 ($r = 0.55$). The 40-year rearrangement used (thick lines, Figure 6.10) was chosen from a large sample of random rearrangements, based on having smallest (near-zero) trends over 2008–2047 (to enable the impact of the addition of a trend to be clearly seen). To generate scenarios with a 20% downward trend, the same adjustment procedure is applied as in Chapter 5 (leading to the thin lines on Figure 6.10).

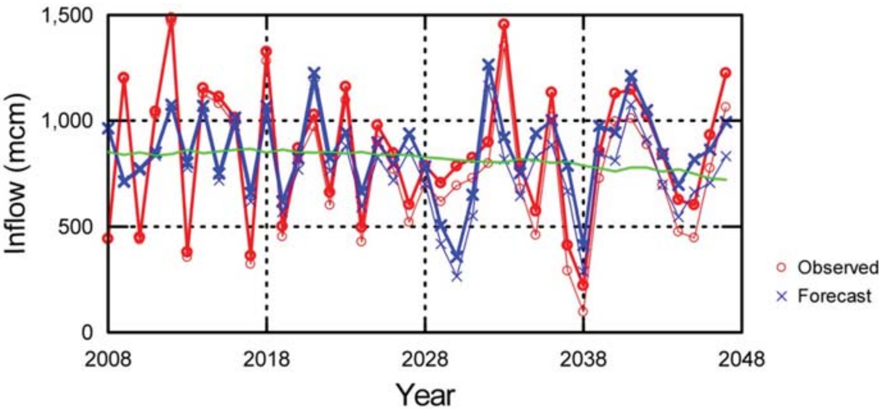

Figure 6.10 Creating forecast-observed inflow scenarios for 2008–2047.
The thick solid lines are a random rearrangement of the forecast-observed pairs for 1968–2007 (therefore correlation is the same, $r = 0.55$). The thin observed line adjusts the observed series to have a downward trend of 20% over 2008–2047. The same adjustment is applied to the forecasts to generate the thin forecast line. Based on the inflow scenario with 20% downward trend, the updated climate normal (i.e. updated climatology) in each year is given by the green line.

In the presence of climate change, for risk management applications, it makes sense in principle to update the estimate of the background climate state each year, based on the recent period that is judged representative. The size and shape of averaging window to use for risk management problems in the presence of varying magnitudes of GC and MDV could be explored within the modeling framework used here. For illustrative purposes, we demonstrate a first order assessment following the standard WMO 30-year averaging window (discussion in Arguez & Vose 2011). The 1968–2007 period is assumed to be stationary, so this is incorporated in performing a 30-year updating procedure in which 1968–2007 values are set to the mean for that period. The updated climate normal for year i (as shown on Figure 6.10, green line) is based only on information available up to year $i–1$ (i.e. the average of the previous 30 years), thereby representing an operationally implementable option.

Figure 6.10 showed seasonal forecasts with no trend, and seasonal forecasts with an adjustment that matches the 20% downward trend of the observed trace. While assuming that seasonal forecasts will be able to perfectly track a trend seems overly-optimistic, assuming zero trend seems overly-pessimistic, especially given examples of seasonal forecast systems that have some ability to track trends in seasonal rainfall and inflows.[2] An intermediate assumption for seasonal forecast trend is to assume that the seasonal forecasts could at least be adjusted by the updated climate normal estimate, such that

$$F_i' = F_i + \overline{Q}_i'$$

where F_i' is the adjusted inflow forecast for year i (now representing a combination of seasonal forecast and updated climate normal), F_i is the original seasonal inflow forecast, $\overline{Q}_i'$ is the updated climate normal for year i, expressed as the departure from the 1968–2007 climatological inflow.

The various combinations of observed, seasonal forecast and updated climate normal estimates (Figure 6.10) were submitted to the reservoir management model to reveal the implications of the different management practices in the presence of zero trend and 20% downward trend in observed inflow. First, a baseline static allocation result is produced for comparison with dynamic allocation approaches. Holding allocation constant in the presence of a 20% downward inflow trend results in a gradual decline in end-of-season reservoir volume (Figure 6.11a, blue line). This finds expression in the summary statistics such as deficit frequency (increasing from 5/40 to 7/40) and maximum deficit (increasing from 281 mcm to 406 mc) (Table 6.3). The following results provide an illustration of the extent to which dynamic allocation might alter such sensitivity to climate trends.

In the presence of the downward 20% inflow trend, water allocation based on updated climatology leads to much less downward trend in end-of-season volume (Figure 6.11a, green line). The water allocation process gradually recognizes the downward trend in inflow and therefore learns to manage the reservoir more conservatively. The overall impression in Figure 6.11a is that responding to updated climate normals can substantially contribute toward making the reservoir sustainable in the presence of an inflow trend of this magnitude (at least in terms of allocations to avoid growing deficit problems).

Next, reservoir sensitivity to the two inflow scenarios is explored when seasonal forecasts are used to inform water allocation. Firstly, the best case scenario is considered, when seasonal forecasts fully track the observed trend. For this case study, the performance is almost unaltered in terms of deficit and spill (compare columns 2 and columns 5 in Table 6.3). The reservoir is able to maintain its

[2] While a GCM-based forecast would likely better capture such trends, there is evidence that statistical seasonal forecasts are able to track trends and longer term variability well (e.g. Ward, 1998; Hamlet & Lettenmeier, 1999), though this should be assessed on a case by case basis.

productivity and reliability, through a gradual adjustment in the allocation, responding to the downward trend in seasonal forecasts (Figure 6.10, thin blue line). The gradual adjustment is small compared to the allocation adjustments that are applied each year to manage the interannual climate variability and which deliver the improved performance of the reservoir through the use of seasonal forecasts.

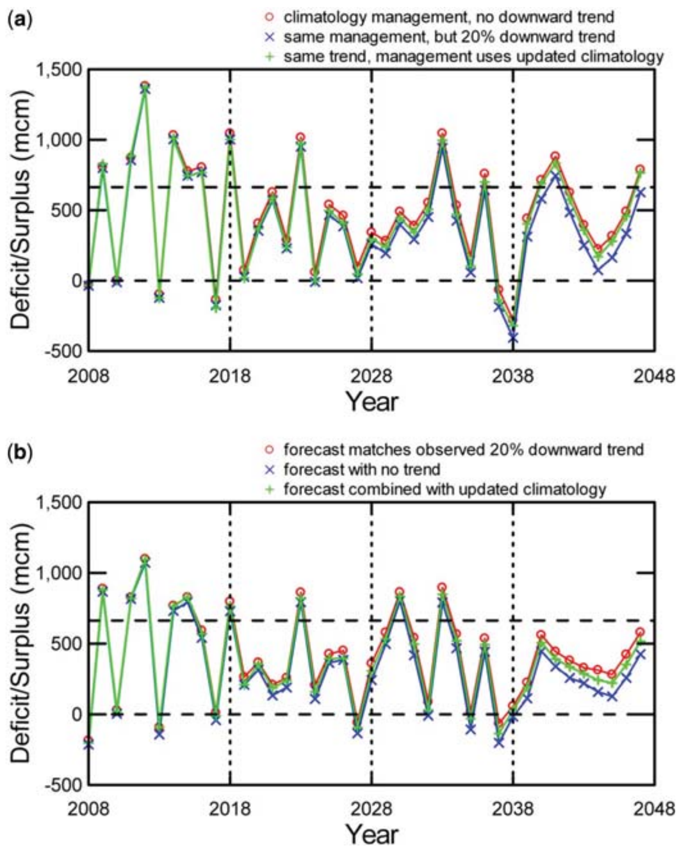

Figure 6.11 End of March deficit/surplus (reservoir volume relative to the critical threshold, the lower rule curve). (a) Management using historical climatology information (for observed of no trend and observed of 20% downward trend), and management using updated climate normals (for observed of 20% downward trend), (b) Management using seasonal forecasts in the presence of a 20% downward trend in the observed inflow. The seasonal forecasts are constructed to track the observed trend to varying degrees. Upper horizontal line is the spill level. Note how generally the use of seasonal forecasts (as seen in (b)) reduces the large spills and large deficits (as seen in (a)), and this benefit is maintained in the presence of a 20% downward inflow trend.

Table 6.3 Reservoir performance under different climate scenarios (no trend compared to 20% downward trend) and different reservoir management.

Inflow scenario:	**2008–2047, no trend in observed inflow**		**2008–2047, downward inflow trend of 20% is imposed on observed**				
Basis for reservoir management:	**Historical climate**	**Seasonal forecast**	**Historical climate**	**Updated climate**	**Seasonal forecast (1)**	**Seasonal forecast (2)**	**Seasonal forecast (3)**
Average end-of-season volume (mcm)	478	421	396	439	413	330	377
Deficit frequency (years)	5	4	7	7	4	8	6
Average deficit (mcm)	−122	−99	−135	−116	−100	−108	−94
Maximum deficit (mcm)	−281	−194	−406	−320	−185	−214	−203
Spill frequency (years)	13	9	10	13	9	9	9
Average spill (mcm)	254	215	254	226	207	159	187
Maximum spill (mcm)	718	440	697	708	436	409	430

In columns 5 to 7, management is based on seasonal forecasts that track the observed trend to varying degrees: (1) forecasts have the same trend as observed, (2) forecasts have no trend, (3) forecasts are combined with updated climatology. All mcm values are departures from the lower rule curve value (348 mcm).

When the seasonal forecasts are not adjusted to track the trend, while many of the benefits do remain (such as the general increase in water allocated, and early warning of many of the drought years through low allocation and therefore avoiding the worst deficits), there are nonetheless problems of a gradually declining end-of-season volume and an increasing deficit frequency. For example, the deficit frequency (8/40) for this case study is actually higher than using historical climatology (7/40) (Table 6.3). The downward trend in end-of-season volume is clearly present (Figure 6.11b, blue line; compare to the red line when seasonal forecasts do track the trend). However, it is reasonable to assume that in many cases, seasonal forecasts could at least contain trend information from an updated climate normals approach. Using such seasonal forecasts to manage the reservoir gives a better performance in terms of deficit frequency and average deficit (Table 6.3, and visually apparent in Figure 6.11b, green line, where the downward trend in end-of-season volume is substantially reduced). This suggests that such an approach is quite effective in managing the 20% downward trend while continuing to extract the benefits from seasonal forecasts, especially in avoiding the worst deficits, and continuing to increase the overall productivity of the reservoir.

To make the best estimates, the results should be averaged over multiple realizations, regenerating the series in Figure 6.10 multiple times and producing averaged results for this Table. While most tendencies appear robust and patterns clear (such as can be seen graphically in Figure 6.11 and Figure 6.12, and in most of the statistics in the Table), measures relying on thresholds such as deficit frequency can be especially sensitive to the particular realization. For example, for the realization presented here, and under a 20% downward trend, compare the Historical Climate results (column 3) and Updated Climate results (column 4). While using Updated Climate gives noticeable improvement in average and maximum deficit, there is actually no improvement in the deficit frequency (7 out of 40 years whether historical climate or updated climate information is used for the water allocation). This is because the marginal deficit years in this particular realization have tended to occur in the first part of the series, when the improvements from updated climate normals are yet to become clearly established.

An additional aspect in these adaptive management experiments is the resulting changes in allocation characteristics. The nature of such changes can contribute to stakeholder dialogues. To illustrate the type of insights that could emerge, we focus on the amount of water allocated to the secondary user (agriculture) in this system. This is the water delivery that is most variable and so is most sensitive to management effects. Based on updated climatology, the amount of water allocated to agriculture is gradually being squeezed to a very small amount by the end of the simulation period (Figure 6.12). The allocations based on the seasonal forecast have a very different character (Figure 6.12). When seasonal forecasts do not track the trend, the allocations gradually become over-aggressive (leading to the increases in deficit frequency). When allocations are based on seasonal forecasts combined with updated climatology, the allocations still vary greatly from year-to-year, but now also gradually become more conservative (Figure 6.12, blue line), leading to a better performance in terms of deficit frequency, while maintaining a higher average allocation to agriculture. The average increase in allocation to agriculture is clearly visible in Figure 6.12, and amounts to 232 mcm (average of blue line) compared to 154 mcm (average of green line). However, years with low expected inflow can lead to very low or zero allocation to agriculture. We advocate this kind of result be considered a contribution to stakeholder dialogue, rather than seeking to promote any specific rigid management system. In practice, very low allocation to agriculture may be viewed as an early warning of increased risk of seriously low inflow levels. This may trigger drought management agricultural practices, and/or flexible strategies able to utilize inflow should it materialize, such as option contracts or reservoir insurance (Brown & Carriquiry 2007). The latter can be an important component of a dynamic water allocation system. This is because with a target reliability of 90%, the water available in the reservoir at the end of March will be greater than that allocated on 90% of occasions. Capacity to respond to allocations revised upwards as the season unfolds can substantially increase system productivity (Sankarasubramanian *et al.* 2009).

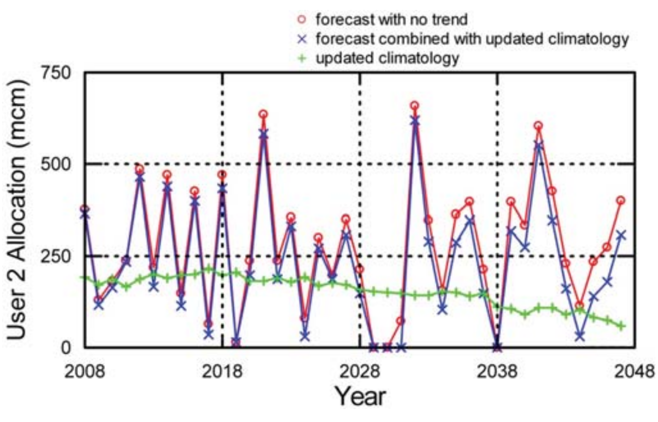

Figure 6.12 Water allocation to user 2 (agriculture) in the presence of a 20% downward trend in inflow. Allocations are based on seasonal forecasts with no trend (red line), seasonal forecasts combined with updated climatology (blue line) and updated climatology alone (green line). All allocations target 90% reservoir reliability for the given year.

Nonetheless, low allocation based on a seasonal forecast is rooted in probabilistic information that genuinely indicates increased risk of low inflow. In the simulation, 2038 provides a case study (see the allocations for this year in Table 6.4) of a very low inflow toward the end of the period when the systematic trend has substantial expression. The allocations based on historical climatology lead to a total deficit of 406 mcm, including a deficit of 209 mcm for the primary priority user (municipal). Using updated climatology provides some softening of the impact, leading to less overall deficit, less of a shock for agriculture, but still the same deficit for municipal. The seasonal forecast combined with updated climatology communicates the increased risk of low inflow by cutting allocation back to zero for agriculture and even substantially below the demand level for municipal. The outcome actually produces slightly more inflow than is allocated, leading to a small surplus of 24 mcm under this management strategy. An accurate seasonal forecast therefore provides the potential to better manage a year like 2038, avoiding sudden onset of severe water shortage as the extreme season unfolds, carrying with it the potential for major impact and lasting damage. In this light, the adaptation benefits of seasonal forecasts in the current model system can be considered conservative estimates, since multi-year impacts of extreme droughts are not explicitly modeled (e.g. see discussion of multi-year impacts of extreme events in Carter *et al.* 2007). In summary, the analysis approach was designed to reveal contrasting sensitivities and system properties during a 20% decline in inflow over a 40-year period. The results have shown that system sensitivity to a 20% downward trend can be influenced substantially through adaptive management, and contrasting options for flexible adaptation can emerge (e.g. as implied by the blue and green lines on Figure 6.12).

Table 6.4 Management case study: The low inflow year of 2038 in the random simulation.

Basis for reservoir management:	Historical climate	Updated climate	Forecast + updated climate
Allocation to municipal	722	722	485
Allocation to agriculture	197	111	0
Total allocation	919	833	485
Total deficit	−406	−320	+24
Municipal deficit	−209	−209	0

All values are in mcm.

Taken together, the findings from our evaluation using a synthetic decision support tool illustrate the nuanced benefits possible from using climate-based seasonal inflow forecasts and updated climate normals. In the explicit presence of trends, it is important to remember that these kinds of evaluations are relatively new and further experiments are needed to see more clearly the outcome patterns, and adaptation benefits, of different management approaches during a climate trend. Results can be hindered by short record lengths, which can lead to small sample sizes unable to provide adequate characterization of the range of climate variability, and uncertainty in future conditions. Additionally, the significant year-to-year variability in the forecast benefits demonstrated above suggests that forecasts alone cannot resolve all climate-related challenges in a reservoir system. The following section offers some possible complementary techniques for making the most of forecasts and mitigating possible risks, particularly in an institutional context.

Section 2: Other techniques for managing climate risks and opportunities in water supply systems

Adjusting decisions related to reservoir releases is a very straightforward and direct approach to the use of forecasts. This section offers other techniques for using climate information to improve the resilience of water supply systems. In general, these are based on good practices from water resources management. These techniques can facilitate integration of climate information (and the advance warning that often results) to support proactive decision making. They can help manage hydroclimatic challenges, such as droughts or floods. Various approaches and some example applications are provided below.

Section 2.1: Managing drought risks to water supply through redundancy (multiple and on-demand sources)

A water system that is dependent on a single source of water is vulnerable to any interruptions to that source. For a surface water system, drought is a primary risk to the ability to supply needed water. If a drought affects a single supply system, there are limited options for providing water. In most cases, the water authority is forced to impose water use restrictions or ration water supplies. This causes hardship on the water users and can impose economic losses on low priority water users, such as in agriculture in many systems. Identifying and accessing multiple sources of water is a way to manage the threat of drought to a single source system. Climate information is useful for designing and managing a multi-source system, and the use of climate information is described in each of the topics below.

Conjunctive use of surface and groundwater

The operation of groundwater and surface water sources together to provide reliable water supply is called *conjunctive use*. Groundwater is commonly exploited as a water supply source and, in some parts of the world where there is little surface water, it represents the only available water source. In many parts of the world, however, surface and groundwater are both available. Surface water tends to be more variable and subject to the occurrence of droughts, while groundwater tends to be relatively stable and subject only to very long-lasting droughts that persist over several years to decades and beyond. However, groundwater is also prone to overuse and, when used exclusively, can result in groundwater mining, which occurs when the extraction rates exceed recharge rates and groundwater levels drop. The different temporal characteristics of these two water sources can be exploited to provide more reliable water supply. Groundwater represents an excellent complement to a surface water system. Groundwater is able to supply water when surface water sources are deficient. In addition, groundwater can serve as water storage when there is excess surface water. In a process called "artificial recharge" the excess surface water can be pumped into existing groundwater aquifers. Used together, these sources can provide reliable water supply that is more resilient in the face of droughts and can help prevent falling groundwater levels. Climate information can help guide decisions regarding when groundwater sources should be utilized and when surface water is expected to be sufficient to allow for artificial recharge.

System connectivity and multiple scale structure

The reliability of a water supply system can be enhanced by increasing the connectivity of the system to other systems. This is typically achieved through the construction of infrastructure, such as canals, aqueducts and pipes so that a system can be supplied by multiple sources. Climate information can be used to choose where to make connections. For example, connections that provide access to water supply sources with different drought regimes will provide added reliability compared to a connection to sources with the same drought regime. Climate information provides the understanding of where drought typically hits and its spatial pattern and extent, so that connections can be made to provide the most reliability. Real options is a planning approach that may be applied in this manner, where small upfront infrastructure investments allow the option to connect systems in the future (Steinschneider & Brown, 2012).

Reliability of water supply and equity in its distribution for agricultural or other uses may also be able to be improved through combining large-scale infrastructure investment with decentralized, small-scale surface storage management. The balance of investment between such large-scale and small-scale storage solutions is a choice that can form part of a climate risk management strategy. Simulation models can be developed to investigate how performance measures (e.g. economic equity and efficiency, resilience, etc.)[3] for different approaches respond to climate change scenarios and varying system management parameters, such as crop choice (e.g. see Lall & Kaheil, 2009). This type of assessment represents an emerging contribution to the field of climate risk management.

Portfolio of water sources

In many cases it will not be possible to identify and make the ideal infrastructure investments necessary to develop additional water sources for single-source water

[3]For more information on criteria and indicators that can help policymakers determine the appropriate scale of water storage projects, see van der Zaag and Gupta (2008).

supply systems. The water may not be available because it is owned by another system or is too expensive to tap. Or additional water may only be needed for a limited amount of time, making it uneconomical to invest in new infrastructure. In such cases it may be possible to build a portfolio of water sources by making agreements or contracts with other water suppliers to be able to purchase their water in times of need. In some river basins, water markets have been established and, these can be exploited to provide additional water sources in times of need. An understanding of a system's vulnerability to drought and the temporal and spatial characteristics of drought are particularly important when designing a portfolio of water supply sources. For example, if the different water supply sources are all affected by the same drought, they will provide little redundancy. It is better, when possible, to design the sources so that they access different river basins, different climate zones and also groundwater, when possible.

Section 2.2: Climate-informed water pricing

The standard approach to managing water supply drought is to curtail water deliveries to the water users. Due to the inconveniences and potential economic losses that may result, this is a situation that is best avoided. Still, on occasion there will not be sufficient water supplies and the delivery of water to users will be curtailed. The manner in which this is done has a large effect on the impacts of the water shortage. The typical approach is to enact uniform cuts on water use and to restrict certain uses, such as outdoor uses. This has the advantage of attempting to provide equity in the availability of water. However, this does not entail equity in the economic damage that is done by the water shortage. A water restriction on outdoor water use, for example, might have little or no impact on a homeowner who can forgo watering the lawn, but may have a very large impact on a business owner whose orchard trees may not survive without watering. For this reason it may be advantageous to adjust the price of water when water is scarce, instead of restricting certain uses of water. Price adjustments can provide incentives for conservative water use.

Water prices can be adjusted to be more expensive during a time of drought, which would provide a disincentive to water use and decrease the actual amount of water used. This allows the water user to decide if a particular use of water is valuable enough to justify water use even in a time of drought. A baseline level of water use should be exempted from the drought pricing so that all water users have access to basic water services without regard to their ability to pay.

Forecasts of drought may be used to adjust prices before the drought occurs. This would be particularly advantageous where agriculture is a major water user and the prices could be adjusted prior to farmers' planting decisions. If the farmer faces high water prices due to increased likelihood of an impending drought, he or she would have an incentive to plant crops that require less water, or to plant a smaller area. Thus, the water demand of agriculture would be consistent with the expected scarcity of water and help the water system manage the drought.

Section 2.3: Other economic mechanisms for drought risk management

The temporary nature of drought means that the responses to drought also can be temporary. Economic mechanisms provide several alternatives for temporary responses to water shortages. Some of these, such as water pricing, have been mentioned above. Another source of water reliability is through *water rights transfers*. The general concept is that a water supply authority could purchase the rights to a quantity of water for use during a shortage. This might be accomplished through a formal *water market* for temporary water transfers. Although water markets are gaining in popularity, many systems continue to rely on administrative water allocation mechanisms such as priority allocation and participatory negotiation. Research results from the state of Ceará in Northeast Brazil suggest that these mechanisms likely result in decreased economic efficiency relative to well-designed water markets, with disparities varying based on the degree of water scarcity (Souza Filho & Brown, 2009).

Rather than operating through a formal water market, a water supply authority might arrange with specific water suppliers individually for the temporary rights to their water. In such a case, an *option contract* might be utilized. An option contract is a contract that gives the buyer of the water the option to buy the water under specific circumstances that are agreed upon in the contract. Often, the buyer pays the water seller for the rights to the option over a long time period, and then pays again for the purchase of the water when the option is exercised. For the option seller, selling the option provides consistent supplemental income in addition to the agreed upon price for exchanging water when the option is exercised.

Option contracts have great potential where agriculture and domestic water supply are both major water users in a region. Since water represents the income and livelihood of agricultural water users, they are often able to accept compensation in exchange for their water rights on a temporary basis. For example, an agricultural water user could forgo planting crops or decide to plant crops that consume less water, and then lease their right to water to a domestic water supply during drought. Typically, the value of water for domestic use is higher than the value of water in agricultural use, which, in principle, makes such exchanges sensible and possible.

There are some examples of the use of options and similar mechanisms within water markets. For example, water options were incorporated with the California Drought Water Bank of 1995, and in agreements between the irrigation districts and the Metropolitan Water District of Los Angeles, California (Jercich, 1997; Howitt, 1998). Michelsen and Young (1993) calculate significant potential gains for water options sold by agriculture to urban water agencies in lieu of purchasing permanent water rights for Fort Collins, Colorado. The Northern Colorado Water Conservancy District is implementing options within their contract system (Kemper & Simpson, 1999). In Camp de Tarragona, Spain, the City of Reus has negotiated to buy water from farmers in times of need, though no option payments are exchanged (Tarrech *et al.* 1999). In general, however, water options have not yet been fully utilized in water market exchanges.

Climate information can improve the economic efficiency of option contracts. For example, a water supplier could use a seasonal climate forecast of impending drought to exercise their water options and purchase water rights before the drought occurs. If an agricultural water user holds the options and the options are exercised prior to the investment in crops, the water can often be purchased more cheaply.

EXAMPLE 6.3: Managing risk of uncertain water supply through water markets and incentive systems

There is a long history of innovative water management in Spain. A group of researchers has been studying how various economic mechanisms could be used to address drought and rainfall patterns in the Guadalquivir River Basin in southern Spain. Water in the basin is used for both irrigation and urban water supply systems, including for the city of Seville. When modeling irrigation decisions for the region, the researchers found that drought conditions imposed significant costs on farmers, and that the costs were exacerbated by over-allocation by water managers during periods of abundant water supply (Iglesias *et al.* 2003). If the users had access to perfect water supply forecasts for an entire year in advance, they could increase gross revenues marginally (around 5%). Introducing a voluntary banking system (i.e. farmers can voluntarily store part of their allocation in the reservoir for use in future seasons) could allow farmers to increase benefits by 32–82%, depending on the supply system (Iglesias *et al.* 2003).

The researchers then explored the development of a spot water market to allow the voluntary temporary exchange of water use among irrigation users. Again, the goal was to use more flexible instruments to reduce risk exposure due to climate variability and highly unreliable water supplies. While allowing limited simple water exchanges between local irrigators was shown to reduce economic costs, extending the market to multiple districts and across users facing varying hydroclimatic risk exposure increased benefits (Calatrava & Garrido, 2005). Specifically, extreme events with the lowest economics benefits were less likely to occur. Thus, the modeled water market for this region allowed farmers to respond to water supply variability across irrigation seasons and reduce overall economic vulnerability (Figure 6.13).

While these water markets were constructed to benefit the farmers relying on irrigation, the modeled systems did not consider urban water needs. In order to account for these competing user demands, Gómez Ramos and Garrido (2004) examined the use of options contracts to transparently transfer risk and compensation between irrigation and urban water users. They found that options contracts represent "a midpoint between permanent right sales and spot water markets, with two additional advantages … on the one hand, option contracts ensure a transparent risk transfer mechanism for a number of years (4–6 may be advisable) … on the other hand, they provide assurance to the farming communities that their livelihoods can coexist with urban demand pressure" (Gómez Ramos & Garrido, 2004; p. 9). In essence, the market is based on a compensating premium applied to the contracts that ensures that a seller is compensated for both the water allocated and the additional risk due to the contract. The researchers recognize that the option pricing remains particularly challenging, and it is this area that could benefit significantly from improved climate forecasting and quantification of the resulting hydroclimatic risk.

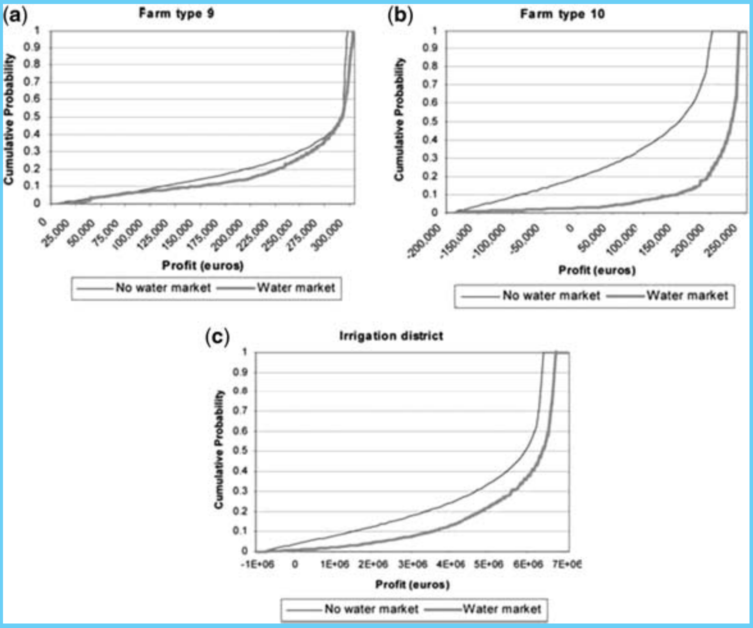

Figure 6.13 Profit probability distributions with and without voluntary water market.
Panels (a) and (b) show the distributions for different farm types, revealing that the benefit of a water market depends on specific irrigation conditions. Panel (c) shows the distribution across the entire irrigation district, demonstrating that net benefits are fairly significant. *Source:* Calatrava and Garrido, 2005.

Section 3: Challenges to the use of forecasts by water managers

Certain types of CRM innovations are being adopted at slower paces, despite simulation of expected benefits. A specific case is the use of seasonal climate forecasts. Foundational studies have identified a variety of causes that contribute to the apparent disconnect between climate information providers and those who would use the information (see World Climate Conference 3, 2009, and the emerging concept of reinvigorated climate services). One major component relates to the "supply side", or the provision of climate information itself. We have learned that stakeholders often find climate information, as currently provided, to be difficult to interpret, of insufficient skill, or on an inappropriate spatial or temporal scale for their decision making needs (Yarnal *et al.* 2006; Hartmann *et al.* 2002; Pagano *et al.* 2002; Rayner *et al.* 2005; Lemos *et al.* 2002). Another major component relates to the *demand side*, or the decision processes used by stakeholders. There are several institutional obstacles that limit the likelihood that water managers would use climate information even if the information was relevant and sufficiently skillful. These obstacles include a traditional reliance on infrastructure, a lack of knowledge regarding how to incorporate new water management methodologies, organizational conservatism, political disincentives to innovation within water management institutions and, in some cases, regulatory constraints on how decisions must be made (Rayner *et al.* 2005).

These challenges make clear some necessary and practical actions needed to ensure that forecasts are more effectively used by the water sector. The primary lesson is the need for close collaboration and trust-building between the forecast provider and the forecast user. Collaboration across these organizational boundaries can lead to co-learning and co-production of climate and risk management knowledge, resulting in the tailoring of climate information to be relevant to user needs and the demonstration of skill in transparent, understandable ways. In addition, it is clear that the fear of unintended consequences of forecast use is a major disincentive. Water managers are fearful that a forecast will be "wrong" and expose the system to additional risk. This can be reduced by the methods of redundancy in water supply and others described above.

The building of knowledge networks has been identified as a key method for improving the uptake of scientific information by stakeholders (e.g. Feldman & Ingram, 2009). Knowledge networks may be described as systems organized to link science and technology to agents who act to attain social goals (NRC, 2005). Sustained interactions between scientists and practitioners provide the opportunity for mutual learning and the understanding needed to produce climate information that is useful (NRC, 2008). Knowledge networks provide conditions that enhance the innovation adoption process, described as a "diffusion of innovations framework". These networks promote awareness and interest and provide opportunities for trial and experimentation. They can serve to reduce complexity and increase the compatibility of climate information. The establishment and sustainability of a knowledge network of water managers and forecast providers may be considered one of the most powerful ingredients for the successful development and provision of useful climate information.

CONCLUDING REMARKS

There are many ways of taking the climate information discussed in this manual and applying it to help manage the hydroclimatic risk and opportunities in a given water supply system. The most appropriate and successful suite of options will depend on the landscape of institutional, physical and financial conditions specific to the system. Whether water managers act directly based on climate information or institutions integrate climate information into the development of economic mechanisms to combat drought, the key outcome is the effective use of the information to inform action that is as anticipatory as possible. Evaluating the possible benefits and consequences of integrating climate information into decision making is critical. Ultimately, the goal is for increased understanding and collaboration between water resources professionals, policy makers and climate science professionals to result in improved climate risk management.

Exercise 5: Managing risks and opportunities for a multipurpose reservoir within an institutional context

Exercise 5 is intended to be conducted in groups. It includes a role-playing component that separates participants into different stakeholder groups and provides guidance for making decisions within a simulated institutional context. The exercise will allow you to make water allocation decisions for a multipurpose reservoir using a forecast for a past year based on a climate-based probabilistic seasonal inflow model. You can then assume the season elapses and update the model using observed inflows from the historical record. Participants are able to both explore the dynamics involved in making decisions using probabilistic forecasts and recognize the possible consequences of these decisions.

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Appendix 1

Planning and decision making

INTRODUCTION

Managing climate risks in a water supply system is a process that requires planning and decision making at multiple scales. This appendix reviews some key concepts and approaches in planning and decision making that are relevant when determining how to integrate climate information.

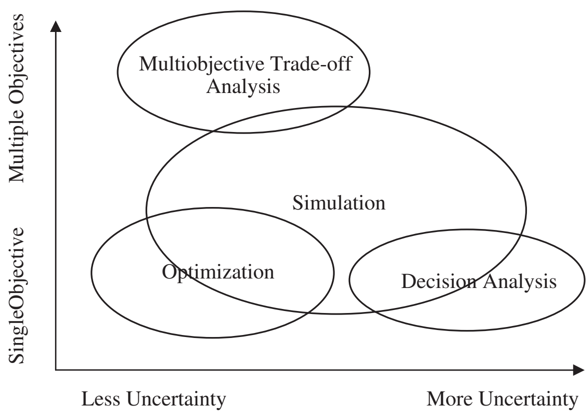

Figure A.1.1 General applicability of decision support techniques for problems with uncertainty and multiple objectives.

Because water is a public good, water resources planning is a complex process requiring consideration of multiple and often conflicting objectives. Due to climate variability, as well as uncertainty in future demographics which drive water demand, good planning also requires consideration of risk and uncertainty. Although many of the objectives of water resources systems cannot be quantified in economic or other quantitative terms, and risks themselves have to be estimated (e.g. based on expert judgment), there are a number of analytical methods that can support decision making and improve the planning process. Several of these are discussed here, including economic benefit analysis, decision analysis, simulation, optimization modeling, and multiobjective trade-off analysis.

Section 1: Economic benefit analysis

Economic benefit (or cost-benefit) analysis is a standard procedure used in planning when the primary benefits (and costs) of alternative designs or plans can be evaluated in economic terms. Examples include revenues from hydroelectric power generation, profits from irrigated agriculture, and reduction in economic damages from flooding. Since benefits and costs accrue over time, a means of converting time series of benefits and costs (or net benefits) to comparable terms is needed. This is conventionally done through the use of a discount rate. Analogous to the interest rate on a loan, the discount accounts for the time value of money, inflation, and any risk associated with future payback. An example calculation is shown in Figure A.1.2.

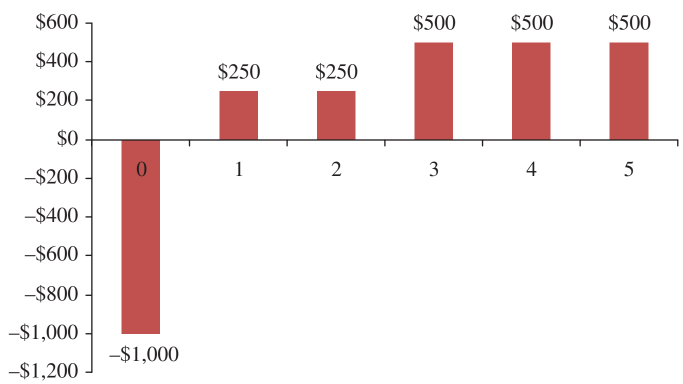

Figure A.1.2 Calculating the net present value (NPV) of a time series of costs and benefits ($i = 7\%$ assuming a discount rate (e.g. inflation rate) of 7% per year). For each time period, t, the value is calculated by dividing the current cost or benefit by $(1 + i)^t$. The NPV is then calculated by summing the value across all time periods.

$$NPV = \frac{-1000}{(1+.07)^0} + \frac{250}{(1+.07)^1} + \frac{250}{(1+.07)^2} + \frac{500}{(1+.07)^3} + \frac{500}{(1+.07)^4} + \frac{500}{(1+.07)^5}$$

$$NPV = -1000 + 233.64 + 218.36 + 408.15 + 381.45 + 356.49 = \$598.09$$

A related approach is called cost-effectiveness analysis. This approach is used when the primary benefits of an alternative plan cannot easily be quantified in economic terms, but can be quantified in other terms. For example, alternative reservoir operating plans may be evaluated based on the reliability of meeting a particular water demand or release target. In this case, an explicit economic value may not be placed on the water use, but benefits are still measured directly in a quantitative way (e.g. the fraction of time the target is met, or the inverse of the expected consequences when the target is not met). Many social and environmental objectives can be quantified in ways other than explicit monetary units. Examples include hectares of habitat restored, in-stream flow rates for environmental purposes, and the number of jobs created.

In applying economic benefit or cost-effectiveness analysis, care must be taken to address equity concerns—that the costs and benefits of the selected plan are "fair" to all stakeholder groups. For example, a plan that ensures nearly 100% reliability for one user group, while providing only "surplus" water to a second group, might be considered "unfair." In some cases, politics may ensure that such inequitable plans or policies are not implemented; however, unequal power among stakeholder groups may prevent this.

There are other limitations and pitfalls of economic benefit analysis. For example, pitfalls can occur in attempting to assign economic value to benefits that are not directly measurable in economic terms, for example, environmental benefits, through survey techniques or various indirect methods. (For details, the reader is referred to texts on environmental economics). Furthermore, traditional cost-benefit or cost-effectiveness analysis has quantified benefits only in terms of expected values, without due consideration of risk and uncertainty. In many cases, risk averse decision makers will sacrifice some expected net benefits in order to reduce the risk of negative consequences.

Section 2: Decision analysis

For cases in which the consequences of various alternatives are highly uncertain, a more general approach known as decision analysis may be applied. Conducting a systematic decision analysis requires the following elements (Ang & Tang, 1990):

(1) A list of all feasible alternatives, including conducting experiments or waiting for additional information, if appropriate;
(2) A list of all possible outcomes associated with each alternative;
(3) An estimate of the probability of each outcome;
(4) An evaluation of the consequences of each alternative under each outcome;
(5) The criterion for decision; and
(6) The systematic evaluation of all alternatives.

These elements can be integrated into a visual decision model known as a decision tree (e.g. Figure A.1.3). The decision tree begins with a decision node (square) which represents the decision to be made. From this node, each alternative is represented by a branch. At the end of each branch, there is a chance node (circular) with branches that represent the uncertain outcomes. A probability must be assigned to each outcome, and the outcomes emanating from a single chance node are considered mutually exclusive and span the entire range of possibilities. Thus, their probabilities sum to unity. Multiple stages of decisions and uncertain outcomes may be represented in the decision tree, but typically only one or two stages are considered in order to keep the computations manageable. Example A.1.1 illustrates a decision analysis problem and its solution using a decision tree.

Example A.1.1: Decision analysis example

A water manager must decide how much water to promise to the Dry Gulch Irrigation District for the coming growing season. River inflows to the reservoir cannot be forecast perfectly, but the following probabilities (Table A.1.1) are estimated:

Table A.1.1 Inflow scenarios.

Hydrologic scenario	Probability
High inflow	0.3
Average inflow	0.4
Low inflow	0.3

Three standard contract amounts can be chosen for the coming growing season: *A* (500 Mm^3), *B* (300 Mm^3), and *C* (100 Mm^3). The value of each of these alternatives under each outcome is given in Table A.1.2. Additionally, the water manager can wait a few months (once inflows are essentially known with certainty) to sign a contract with the irrigation district, but the value of each contract decreases by $1 million due to the inability of the irrigators to plan properly.

Table A.1.2 Outcome Values ($ million).

	Inflow scenario		
Contract	High	Average	Low
A	5.0	2.0	−5.0
B	1.5	3.5	−1.0
C	0.5	1.0	1.5

Figure A.1.3 is the decision tree used to determine the alternative with the maximum expected value. In this case, due to the large uncertainty in flows, the optimal strategy is to wait and see whether the inflow will be high, low, or about average.

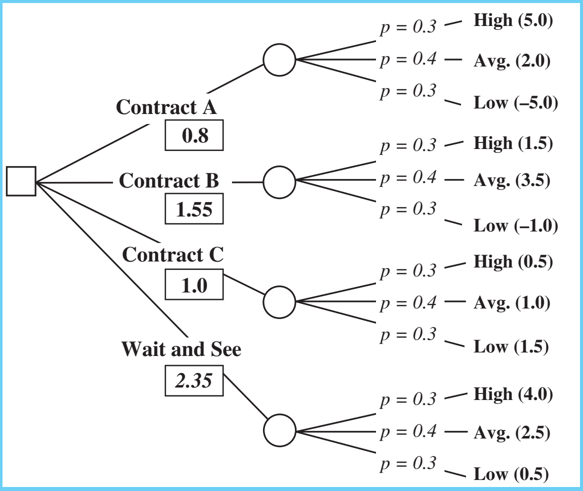

Figure A.1.3 Decision tree for selecting the optimal water contract. Expected value of each alternative is shown in the box. The decision tree begins with a decision node (square) which represents the decision to be made. From this node, each alternative is represented by a branch. At the end of each branch, there is a chance node (circular) with branches that represent the uncertain outcomes. A probability (p) is assigned to each outcome, and the outcomes emanating from a single chance node are mutually exclusive and sum to 100%.

Section 3: Simulation and optimization modeling

For many complex problems, evaluating or predicting the consequences of alternatives is best done using a computer (numerical) simulation model. To be useful, such a model must adequately represent the key physical features of the problem and the decisions to be made, and then predict the outcomes of the decisions in quantitative terms that can be used for evaluation. Simulation models can represent complex physical, chemical, and biological relationships, and they can utilize large amounts of data covering a range spatial and/or temporal scales (Figure A.1.4). Through simulation modeling it is also relatively easy to represent uncertainty in the data or underlying physical relationships. However, when using a complex simulation model, evaluation of decisions requires a trial and error process, which can be time-consuming. In such cases, a simplified optimization model may be a useful complement to simulation as a means of identifying promising alternatives.

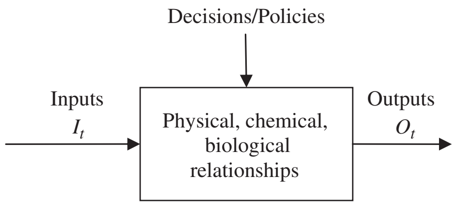

Figure A.1.4 Conceptual diagram of a water resources simulation model.

Optimization modeling is useful when there are so many alternatives that it is not possible to analyze all of the outcomes, or even identify all of the potentially good alternatives, through simulation or decision tree modeling. Formulating an optimization (mathematical programming) model requires the definition of decision variables, which represent the decisions to be made, and an objective function, which represents the criterion for solution. For many problems it is also necessary or convenient to define one or more constraints, which represent either laws of the natural world which cannot be violated, resource constraints, or goals which have very high priority. (Typically, the constraints are the same as, or very similar to, the physical relationships embedded in the simulation model.)

Shown below is a simple linear programming (LP) model, defined as an optimization model in which the objective function and constraints are all linear. LP models can be solved using an algorithm known as the simplex method (e.g. Hillier and Lieberman, 2005). Optimization models may also be formulated with nonlinear objectives and constraints, as well as discrete decision variables. (As an example, consider the problem of scheduling hydroelectric power generation, which is a function of both discharge and reservoir levels and involves switching discrete generator units on and off.) Such problems may be much more computationally demanding than LP models, and thus simplifications are often required. Below is an example of a linear program with the solution shown graphically in Figure A.1.5.

$$\text{Max } Z = 3x_1 + 5x_2$$

subject to

$$3x_1 + 2x_2 \leq 18$$

$$x_1 \leq 5$$

$$2x_2 \leq 12$$

$$x_1, x_2 \geq 0$$

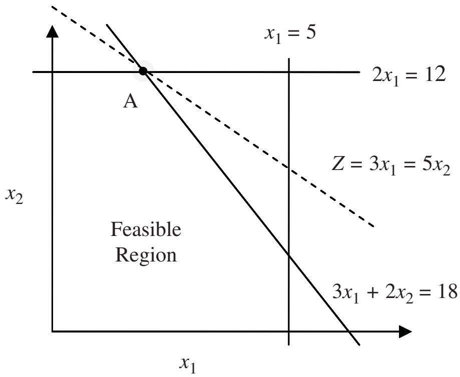

Figure A.1.5 Simple linear programming model with graphical solution (Point A).
Source: Adapted from example in Hillier & Lieberman (2005).

Section 4: Multiobjective decision making

Since water resources systems provide multiple benefits, which are valued differently by different stakeholders, some trade-offs must always be made. Although final decision making is often a political process, there are a number of analytical methods available for identifying efficient trade-offs. The goal of efficient trade-off analysis is to identify feasible solutions that cannot be improved with respect to one objective without harming another objective. Such solutions can be represented on a graph as an "efficient frontier," as shown in Figure A.1.6.

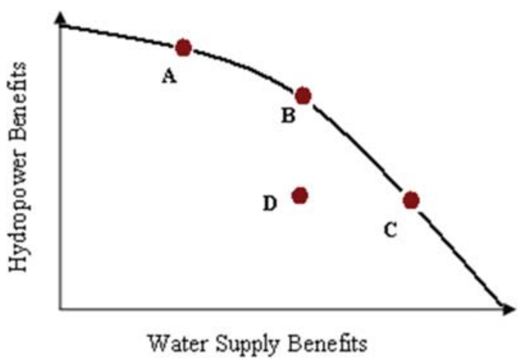

Figure A.1.6 Trade-off analysis for two objectives.
Solutions A, B, and C represent efficient solutions. Solution D represents an inefficient, or dominated, solution.

Several methods are available for generating efficient frontiers using optimization models (e.g, Loucks *et al.* 2005). One approach is to apply weights to the terms in the objective function representing the multiple objectives, and then adjust the weights to generate multiple efficient solutions. For example, a weighted objective function for irrigation and hydropower benefits would be formulated as follows:

$$\text{Max } Z = w_1 f_{\text{irr}}(\mathbf{X}) + w_2 f_{\text{hp}}(\mathbf{X})$$

where $f_{\text{irr}}(X)$ is a function defining irrigation benefits, $f_{\text{hp}}(X)$ is a function defining hydropower benefits, and w_1 and w_2 are weights placed on the two benefit functions. Alternatively, an approach known as the constraint method may be used to generate trade-offs. With this approach, one objective is formulated as a constraint, and the right-hand-side value of the constraint is varied in order to generate multiple efficient solutions. For example, hydropower benefits may be formulated in a constraint as follows:

$$\text{Max } Z = f_{\text{irr}}(\mathbf{X})$$

subject to

$$f_{\text{hp}}(\mathbf{X}) \geq f_{\text{hp}}^{\text{min}}$$

where $f_{\text{hp}}^{\text{min}}$ is the minimum desired hydropower benefit, which is varied to generate trade-offs.

In cases where there are more than two objectives, or it is not possible (or desired) to define a mathematical objective function, various performance measures associated with the objectives may simply be presented in a matrix format. An example is Table A.1.3, showing preliminary results from three proposed plans for managing the Lake Ontario-St. Lawrence River system in the United States and Canada (International Study Board, 2006). Economic benefits are relative to the expected benefits under the current operating plan. Environmental benefits are not quantified economically, but are scaled to the benefits under the current plan, which has an environmental index of 1.0.

Table A.1.3 Summary of plan results in a matrix format. Red *values indicate net losses.*

(Average Annual benefits in millions of dollars)	Plan A	Plan B	Plan D
Environment Index	1.13	1.41	1.03
Shoreline Property	−**$1.10**	−**$2.88**	$.13
Commercial Navigation	$2.27	$1.96	$1.95
Recreational Boating	$3.18	−**$0.87**	$1.95
Hydroelectric	$5.21	$6.11	$1.02

Source: *International Study Board (2006).*

Based on results such as these, individual decision makers will form their own criterion for decision. Some may choose to weight the objectives, while others may seek a solution which provides some minimum level of benefits for all objectives. For instance, placing equal weights on all objectives would lead to selection of Plan A, while a large weight on the environment would lead to selection of Plan B. Some decision makers may prefer Plan D, however, since it increases benefits in all areas in a more equitable manner.

Example A.1.2: Example of multiobjective decision making

An optimization model is applied to help develop monthly operating rules for a reservoir with two main benefits: irrigation supply and hydroelectric power generation. Inflows to the reservoir are highly variable, with a distinct rainy season and dry season occurring in most years. Hydroelectric energy can be generated throughout the year by releasing water through the turbines, up to 80 Mm^3/mon, with the following function approximating the amount of energy generated in each month:

$$P = 0.01 * QS^{0.7}$$

where Q is the hydropower release (Mm^3/month) and S is the storage in the reservoir (Mm^3).

Irrigation occurs only in the dry season, January-April, with the following function defining agricultural production in a given year, y:

$$A = 100\,[\min(R_1, R_2, R_3, R_4)]^{0.5}$$

where $R_1, \ldots, R_4$ are the monthly dry-season releases for irrigation demands. Releases for irrigation demands occur through a separate outlet and cannot be used for hydroelectric power generation.

To evaluate trade-offs between agricultural production and power generation, the following optimization model is solved with a range of weights placed on the two benefit functions:

$$\text{Max } Z = w_1 \sum_{m \in M} P_m + w_2 \sum_{y \in Y} A_y$$

subject to

$$S_{m-1} + I_m - R_m = S_m$$

$$Q_m \leq Q^{\max}$$

$$S \leq S^{\max}$$

$$Q_m, R_m, S_m \geq 0$$

where I_m are the monthly inflows to the reservoir, and S_m is the reservoir storage at the end of period m.

Some results of the multiobjective trade-off analysis are shown in Figure A.1.7. This shows that the maximum hydropower benefits are approximately 4400 MWh, though any generation greater than 4300 MWh results in a significant decrease in irrigation benefits. Similarly, agricultural yields of greater than 4000 tons can be achieved, but at the expense of large losses in hydropower benefits. Based on these results, it appears that a reasonable multiobjective solution is to generate approximately 4300 MWh of electricity and irrigate to achieve a total yield of approximately 3800 tons (Point A).

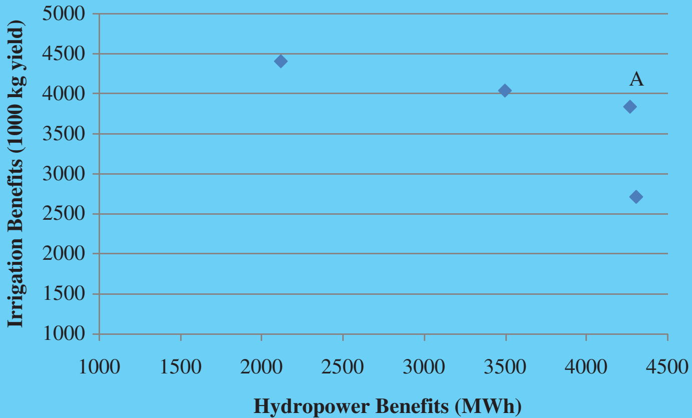

Figure A.1.7 Efficient frontier for irrigation and hydropower benefits from a multipurpose reservoir.
Point A illustrates the most appropriate multiobjective solution.

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Appendix 2

Assessing water demand

Sound management of climate risks is dependent on an awareness of water demand realities. This appendix offers a brief review of some of the important concepts regarding forecasting water demand.

Most empirical models for water demand forecasting have been developed for metered municipal and industrial (M&I) water systems, with variables such as population (or number of households), price, income, and climatic variables (precipitation and temperature) used to predict water use (e.g. Mays and Tung, 1992). A simple example of such a model is a linear regression model of the form:

$$Q = a_0 + a_1x_1 + \ldots + a_mx_m + \varepsilon \tag{A.2.1}$$

where Q is the predicted water use, x_i are the explanatory variables (population, price, etc.), a_i are the fitted coefficients, and ε is the error in the forecast. Assumptions of this approach include the following: (1) the explanatory variables are determined independently of water use (the dependent variable); (2) the explanatory variables are not strongly correlated with each other; and (3) the errors have an expected value of zero, constant variance, and are uncorrelated. An example is shown in Figure A.2.1.

Since water use often has a seasonal component, coefficients as in (1) may be estimated for each month or season. Alternatively, more complex statistical models including harmonic (sinusoidal) functions may be used. If the price of water is determined by market conditions, that is, it is a function of demand, then a system of simultaneous equations is more appropriate than a single regression equation, which assumes one-way causality. For more details on M&I water demand modeling the reader is referred to Mays and Tung (1992).

Agricultural water demand may also be estimated using a statistical model such as Equation (1). However, a more common approach is to use a mathematical programming approach which attempts to model farmers' desire to maximize production, or profits. In this approach, the selection of crops, the area to allocate to each crop, and the amount of water to apply are considered the decision variables, and mathematical functions are developed to relate water application to production (e.g. Griffin, 2006). A general form of a mathematical programming model for agricultural water demand is as follows:

$$\text{Max}\, Z = \sum_i p_i x_i - c_0 Q \tag{A.2.2}$$

subject to

Production functions: $x_i = f(q_i) \times A_i \quad \forall i$

Total water use: $\sum_i q_i = Q$

Total water available: $Q \leq Q^{\max}$

Total land available: $\sum_i A_i = A^{\max}$

Non-negativity: $q_i,\, x_i \geq 0.$

where Z is the total profit, x_i is the production of crop i, p_i is the market price of crop i, Q is the total water use, c_0 is the unit cost of water, A_i is the land allocated to crop i, $Q^{\max}$ is the total water available, and $A^{\max}$ is the total land available.

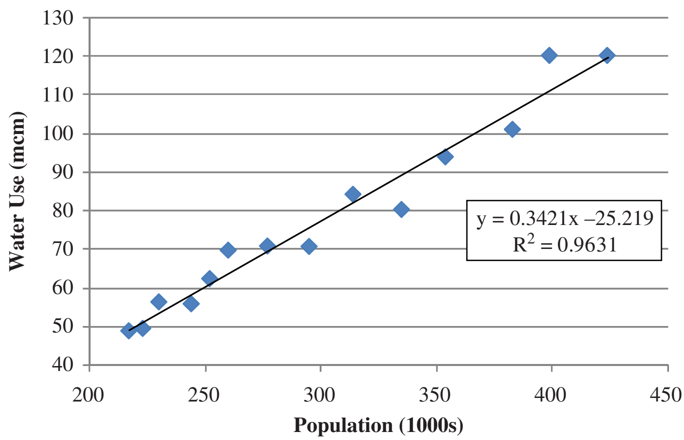

Figure A.2.1 Linear regression water demand model using annual water use data for Austin, Texas, for the years 1965–1985. *Source:* Adapted from Mays and Tung (1992).

The model given by (A.2.2) is a short-term water demand model, based on fixed technology and assuming water is the primary input for production. In the long-term, farmers can invest in more efficient irrigation technologies, essentially changing the production function $f(q)$. Another limitation of this model is that it assumes precipitation and water availability are known, and thus it does not account for hydroclimatic risk. In reality, farmers' decisions are often strongly affected by risk, and thus the decision making framework is broadened to include alternatives such as purchasing insurance or options contracts, and giving up some expected profit in order to reduce risk (e.g. through selection of drought-resistant crops).

In many water systems, the "demands" for water include environmental purposes, such as maintaining stream habitat or adjacent wetlands functions. Traditionally, environmental flow objectives have been specified simply as minimum flow targets or "requirements." Scientists have learned, however, that maintaining ecosystem functions actually requires much more complex patterns of flow, including seasonally varying flows and some extreme high flows. Due to the complexity of ecosystems, a management goal for some systems is to reproduce natural flow patterns, assuming that these will be optimal for protecting the current ecosystem. Although economic valuation techniques do exist for environmental benefits, these are beyond the scope covered here. The interested reader is referred to Griffin (2006) or a text on environmental economics.

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Water resources systems provide multiple services and, if managed properly, can contribute significantly to social well-being and economic growth. However, extreme or unexpected hydroclimatic conditions, such as droughts and floods, can adversely affect or even completely interrupt these services. This manual seeks to provide knowledge, resources and techniques for water resources professionals to manage the risks and opportunities arising from hydroclimatic variability and change.

Managing Climate Risk in Water Supply Systems provides materials and tools designed to empower technical professionals to better understand the key issues in water supply systems. These materials are part of a suite of resources that are developed to share climate risk knowledge related to a range of sectors and climate-related problems.

The text motivates students by providing practical exercises and it stimulates readers or workshop participants to consider options and analyses that will highlight opportunities for better management in the water systems in which they are stakeholders.

Managing Climate Risk in Water Supply Systems provides a hands-on approach to learning key concepts in hydrology and climate science as they relate to climate risk management in water supply systems.

The primary audience is technical professionals in water resources management and provides a practical approach to training.

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