Probabilistic scenario-based decision making for water resources planning and management

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To My Family

Summary

Uncertainty is an unavoidable part of decision making. Decisions always have to be made before perfect knowledge on their consequences is known. However, there is no 'perfect knowledge' in hindsight. To research uncertainty and take actions proactively becomes the challenge to scientists and decision makers. In water resources planning and management, uncertainty is presenting at all stages of planning, developing and managing a water system (Loucks, Van Beek et al. 2005). The water systems are dynamically driven by factors such as climate, environment, demographics, socio-economy, technology, policies and regulations, etc. For example, climate change will affect hydrological and water conditions such as rainfall, temperature, water availability for irrigation; socio-economic development causes the change of water demand. However, the variation of these driving forces is unknown and beyond the control of decision makers, so as their impact on water systems. To plan and manage water systems without addressing uncertainty will invite surprises and potential risk subject to unexpected consequences and losses. Therefore, the objective of this thesis is to contribute knowledge to decision making under uncertainty for water resources planning and management.

Scenarios have been widely used to explore uncertainty for long-term strategic planning. Scenarios are defined as "a coherent and plausible description of possible future states of the world" by the IPCC. They are distinguished from the deterministic or most-likely prediction of future states. Scenario-based approaches have been applied largely to analyse future water-related issues, and support water managers and decision makers to put forward strategies for potential problems. Two criteria 'robustness' and 'rationality' are proposed for decision making in face of uncertainty. Unlike traditional decision analysis which makes decisions based on the 'most-likely' futures, robust decisions are those who perform satisfactorily over a wide range of plausible future states. Rationality was usually modelled to maximize the expected profits in economic terms. Von Neumann and Morgenstern (1947) added the risk attitudes and satisfaction of decision makers to economic outcomes, and introduced expected utility theory to model rationality as maximizing the expected utility. To apply scenario-based approaches to support decision making in a rational and robust way, the crucial task is to develop scenarios that can describe and quantify future states under uncertainty.

Two research questions are raised in the research:

(1) How to develop scenarios for future water circumstances to cope with uncertainty?

(2) How to make robust and rational decisions based on the developed scenarios?

Scenarios are defined as qualitative storylines about the future, however, quantitative projections and numerical information should be included to inform decision making. Traditional scenarios were quantified according to each storyline, and leaves out possible situations in between them. The ignorance of in-between scenarios constrains the explorative characteristic of scenarios. Besides, each storyline is assumed to be equally likely without attaching probabilities. Future states with equal chance are not realistic, and it forces decision makers to pick up any scenario arbitrarily. Conversely, the application of probabilities encourages representing uncertainty and explaining assumptions behind scenarios explicitly. It is also more approachable for risk quantification, and informs decision makers the different chances of future situations. The thesis advances scenario development by combining numerical information and attaching probability distributions.

Probability distributions of future states can only be estimated subjectively, and they are highly conditional on the assumptions being made. Bayesian probabilities and expert judgement are two main techniques to combine subjective probabilities and scenarios. Subjectivity cannot be avoided or stopped when talking about uncertainty and the important thing is to make the assumptions and expert judgement about scenarios as explicit and transparent as possible. Besides, the principle of Maximal entropy can be used to choose probability distributions with the largest uncertainty. To estimate climate change impact on water availability in the Yellow River Basin (YRB), China in the next 30 years, probabilistic scenarios of water availability were generated which are based on the climate scenarios (precipitation and temperature) based on the projections of General Circulation Models (GCMs). To investigate socio-economic development impact on water demand in the Yellow River Delta (YRD), China, probabilistic scenarios of water demand were developed using expert judgement. Four storylines comprising two extremes (urbanization speed-up/ agriculture intensive, water-saving/ water consumptive) were constructed to describe the future development of the YRD. An existing expert elicitation technique, i.e. the SHELF method, is used to elicit prior probabilities of socio-economic driving variables from local experts. Probability distributions from individual experts are then aggregated, and correlations between different variables are taken into account by using a multivariate probability distribution based on the Gaussian Copula.

The thesis developed the probabilistic scenario-based decision making framework to handle uncertainties and support decision making in a systematic, robust and rational manner. The framework relies on a full probabilistic distribution of scenarios and outcomes, and ranks decision alternatives based on expected utility theory. The framework not only investigated the monetary objective, but also further engaged the decision makers by investigating their preferences and risk attitudes (risk averse, risk neutral, risk taking) under uncertainty. The risk attitudes of decision makers were modelled using a negative exponential utility function. The decision making framework was applied for a case study of long-term water resources planning and management in the YRD. Evaluation and ranking of candidate strategies was performed against the full probability distribution of water supply and demand scenarios. Sensitivity analysis was performed to test the robustness of the decisions with respect to uncertain factors such as water supply and demand, market prices and the risk attitudes of decision makers.

In summary, the thesis contributes knowledge on uncertainty management and decision making, which includes: achieve better understanding of the state-of-the-art in scenario science; advance scenario development – from qualitative storylines to quantitative projections, discrete states to continuous states, equal- likelihood states to probabilistic states; develop the probabilistic scenario-based decision making framework to handle uncertainties and support decision making in a systematic, robust and rational manner; taking into account risk from both the engineers' and decision makers' perspectives; and analyse the influence of decision makers' risk attitudes on the choice of decisions.

Samenvatting

Onzekerheid is een onvermijdelijk onderdeel van besluitvorming. Beslissingen moeten altijd worden gemaakt voordat perfecte kennis over de gevolgen daarvan bekend is. Echter, er is geen 'volmaakte kennis' achteraf. Om de onzekerheid te onderzoeken en proactief maatregelen te treffen wordt de uitdaging voor wetenschappers en beleidsmakers. In de planning en beheer van watervoorraden is onzekerheid in alle stadia van planning, ontwikkeling en beheer van een watersysteem aanwezig (Loucks, Van Beek et al.. 2005). De watersystemen worden dynamisch gedreven door factoren zoals het klimaat, milieu, demografie, socio-economie, technologie, beleid en regelgeving, etc. Bijvoorbeeld: klimaatverandering zal de hydrologische- en wateromstandigheden zoals regenval, temperatuur, de beschikbaarheid van water voor irrigatie beïnvloeden; sociaaleconomische ontwikkeling zorgt voor een verandering in de vraag naar water. Echter, de variatie van deze drijfveren is onbekend en buiten de controle van beleidsmakers, net als hun impact op watersystemen. Het plannen en beheren van watersystemen zonder het aanpakken van onzekerheid nodigt uit tot verrassingen en mogelijke risico’s met onverwachte gevolgen en verliezen. Het doel van dit proefschrift is daarom kennis bij te dragen aan besluitvorming onder onzekerheid voor water resources planning en beheer.

Scenario's zijn op grote schaal gebruikt om de onzekerheid voor strategische planning op lange termijn te onderzoeken. Scenario's zijn gedefinieerd als "een samenhangend en aannemelijk beschrijving van mogelijke toekomstige toestanden van de wereld" door het IPCC. Ze onderscheiden zich van de deterministische of meest waarschijnlijke voorspelling van toekomstige toestanden. Op scenario's gebaseerde benaderingen zijn grotendeels gebruikt om toekomstige water gerelateerde vraagstukken te analyseren en om waterbeheerders en beleidsmakers te ondersteunen om strategieën naar voren te brengen voor mogelijke problemen. De twee criteria 'robuustheid' en 'rationaliteit' zijn voorgesteld voor besluitvorming met onzekerheid. In tegenstelling tot traditionele beslissingsanalyse die beslissingen maakt op basis van de 'meest waarschijnlijke' toekomsten, gedragen robuuste beslissingen zich naar wens over een breed scala van plausibele toekomstige staten. Rationaliteit was meestal gemodelleerd om de verwachte winsten in economische termen te maximaliseren. Von Neumann en Morgenstern (1947) voegde de risico-attitudes en tevredenheid van besluitvormers toe aan economische resultaten, en introduceerde verwachte nutstheorie om rationaliteit te modelleren als het

maximaliseren van het verwachte nut. Om op scenario's gebaseerde aanpakken toe te passen om besluitvorming te ondersteunen in een rationele en robuuste manier, is het cruciaal om scenario’s te ontwikkelen die de toekomstige staten kunnen beschrijven en kwantificeren onder onzekerheid.

Twee onderzoeksvragen worden gesteld in het onderzoek:
(1) Hoe kunnen we scenario's voor toekomstige water omstandigheden ontwikkelen om met onzekerheid om te gaan?
(2) Hoe kunnen we robuuste en rationele beslissingen nemen op basis van de ontwikkelde scenario's?

Scenario's worden gedefinieerd als kwalitatieve verhaallijnen over de toekomst, maar kwantitatieve prognoses en numerieke gegevens moeten worden meegenomen om de besluitvorming te informeren. Traditionele scenario's werden gekwantificeerd op basis van elke verhaallijn apart, en laat mogelijke situaties weg die tussen hen ligt. De onwetendheid van de tussenin scenario's beperkt de exploratieve kenmerk van scenario's. Bovendien wordt verondersteld dat elk verhaallijn even waarschijnlijk is zonder daaraan verbonden waarschijnlijkheden. Toekomstige toestanden met gelijke kans zijn niet realistisch, en het dwingt besluitvormers scenario’s willekeurig uit te kiezen. Omgekeerd moedigt het toepassen van waarschijnlijkheden het representeren van onzekerheid aan en het expliciet uitleggen van veronderstellingen. Het is ook meer toegankelijk voor het kwantificering van risico, en het informeert beleidsmakers over de verschillende waarschijnlijkheden van toekomstige situaties. Het proefschrift bevordert scenario-ontwikkeling door het combineren van numerieke gegevens en het aanbrengen van kansverdelingen.

In tegenstelling tot frequentists die waarschijnlijkheden schatten aan de hand van enorm veel waargenomen data, kunnen de kansverdelingen van toekomstige toestanden alleen geschat subjectief worden, en zijn ze zeer afhankelijk van aannames. Bayesiaanse waarschijnlijkheden en *expert judgement* zijn twee belangrijke technieken om subjectieve waarschijnlijkheden en scenario's te combineren. Subjectiviteit kan niet worden voorkomen of gestopt wanneer het over onzekerheid gaat, en het belangrijkste is om de aannames en *expert judgement* over scenario’s zo expliciet en transparant mogelijk te maken. Daarnaast kan het principe van maximale entropie worden toegepast om kansverdelingen te kiezen met een zo groot mogelijke onzekerheid. Om de impact van klimaatverandering in te schatten op de beschikbaarheid van water in de Gele Rivier Bekken (GRB) in China voor de komende 30 jaar, werden probabilistische scenario's van de beschikbaarheid van water gegenereerd die gebaseerd zijn op de klimaatscenario's (neerslag en temperatuur) op basis van de projecties van *General Circulation Models* (GCM's). Om de invloed van sociaaleconomische ontwikkeling op de vraag naar water te onderzoeken in de Gele Rivier Delta (GRD) in China, werden probabilistische scenario's van de vraag naar water ontwikkeld met behulp van *expert judgement*. Vier verhaallijnen bestaande uit twee uitersten (versnelling van verstedelijking / landbouw intensief, waterbesparend / water consumptief) werden geconstrueerd om de toekomstige ontwikkeling van de GRD te beschrijven. Een bestaande expertbevragingtechniek, namelijk de *SHELF* methode wordt gebruikt om a priori waarschijnlijkheden van de sociaaleconomische stuwende variabelen van lokale experts te verkrijgen. Kansverdelingen van individuele deskundigen worden vervolgens samengevoegd, en correlaties tussen de verschillende variabelen worden verdisconteerd met behulp van een multivariate kansverdeling op basis van de Gaussian copula.

Het proefschrift ontwikkelde het kader voor op scenario's gebaseerd probabilistische besluitvorming om met onzekerheden om te gaan en om besluitvorming te ondersteunen in een systematische, robuuste en rationele manier. Het kader is gebaseerd op een volledige probabilistische verdeling van scenario's en uitkomsten, en rangschikt beslissingsalternatieven op basis van verwachte nutstheorie. Het kader heeft niet alleen onderzoek gedaan naar de monetaire doelstelling, maar heeft ook de beslissers erbij betrokken door het onderzoeken van hun voorkeuren en risicohouding (risico ontwijkend, risico neutraal, risico nemend) onder onzekerheid. De risicohoudingen van beslissers werd gemodelleerd met behulp van een negatief exponentiële nutsfunctie. Het besluitvormingskader werd toegepast op een case study van langetermijnplanning van watervoorraden en management in de GRD. Evaluatie en rangschikking van kandidaat-strategieën werd uitgevoerd tegen de volledige kansverdeling van vraag en aanbod naar water scenario's. Gevoeligheidsanalyse werd uitgevoerd om de robuustheid van de gekozen beslissing te testen ten opzichte van onzekere factoren zoals de vraag en aanbod naar water, de marktprijzen en de risicohouding van beleidsmakers.

Abbreviations

CDF	the Cumulative Distribution Function
CMWR	the Chinese Ministry of Water Resources
DREAM_ZS	DiffeRential Evolution Adaptive Metropolis algorithm
EEA	the European Environment Agency
FSD	the First-Degree Stochastic Dominance
GCMs	General Circulation Models
GDP	Gross Domestic Product
GHG	GreenHouse Gas
GWP	Global Water Partnership
GWO	the Global Water Outlook
GWF	Global Water Futures
GBN	the Global Business Network
IPCC	Intergovernmental Panel on Climate Change
IPCC-SRES	IPCC Special Report: Emissions Scenarios
IWRM	Integrated Water Resources Management
MA	the Millennium Ecosystem Assessment
MC	Monte Carlo
MCMC	the Markov Chain Monte Carlo
MSE	Mean Square Error
PDF	the Probability Density Function
POME	the Principle Of Maximum Entropy
SAHRA	Center for Sustainability of Semi-Arid Hydrology and Riparian Area
SCENES	Water Scenarios for Europe and for Neighbouring States
SD	the Stochastic Dominance
SHELF	the SHeffield Elicitation Framework
SSD	the Second-Degree Stochastic Dominance
TSD	the Third-Degree Stochastic Dominance
UNEP	the United Nations Environment Programme
WF	Water Footprint
WWV	the World Water Vision
YR	the Yellow River
YRB	the Yellow River Basin
YRD	the Yellow River Delta
YRCC	the Yellow River Water Conservancy Commission

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Chapter 1 Introduction

1.1 Water Resources planning and management

Water resources planning and management refers to making decisions and taking actions to solve water-related problems and obtain benefits from the use of water resources. Water-related problems can be caused by too much, too little water, or by water of low quality due to pollution. These problems can cause great damage and loss of people's wealth, health, or even lives, when no careful planning and management takes place in a forward looking manner. The task of water resources planning and management is to take actions to handle these problems proactively and reactively, in order to avoid loss and obtain benefit economically and socially. The scope of water resources planning and management involves influencing and improving the interaction and integration among three independent and dynamic subsystems: natural resources subsystem, socio-economic subsystem, and institutional subsystem (Loucks, Van Beek et al. 2005). Integrated water resources management (IWRM) was introduced to systematically consider the three subsystems and manage water resources in dimensions of water resources, water users, and their temporal and spatial scales (Savenije and Van der Zaag 2000, Savenije and Van der Zaag 2008), for the sake of equitable, efficient and sustainable development of water, land and other environmental resources (Calder 1998, GWP 2000, Loucks, Van Beek et al. 2005).

However, the subsystems are continuously changing, for example, the changing relation between anthropological development and water in the Anthropocene has been reviewed by (Savenije, Hoekstra et al. 2013). Unsurprisingly, they will continue the changing in the future, thereby impacting water resources. The future state of the water system is dynamic and driven by many variables from the changing subsystems; e.g. climate, environment, demographics, socio-economy, technology, policies and regulations, water management infrastructure, etc. For instance, climate change and aging infrastructures will impact water supply. Population growth and urbanization will impact water demand. The shifts of the social preferences and values will also impact water policy. These driving forces are developing in uncertain ways beyond the control of scientists and decision makers, and the way they drive the water systems are unknown as well (Mahmoud 2008). The challenge for water resources planning and management is that both the changing subsystems and their impact on water systems cannot be known or understood completely and accurately in either short or long term. Decisions have to be made for the immediate future while considering their long-term impact.

Uncertainty is present in all stages of planning, developing, and managing a water system (Loucks, Van Beek et al. 2005). Failure to address uncertainty in decision making activities invites potential risk subject to unexpected consequences or losses. This thesis is about decision making under uncertain future circumstances for water resources planning and management. Decision making under uncertainty refers to the act of choosing one decision among two or more decision alternatives when the outcomes of those decision alternatives are uncertain (Schultz, Mitchell et al. 2010). This thesis focuses on building an integrated framework for explicitly addressing uncertainties and establishing decision rules for ranking decision alternatives in the decision making process.

1.2 Decision making under uncertainty in water resources planning and management

Uncertainty has been studied extensively and classified from different perspectives and disciplines (e.g.,Kahneman and Tversky 1982, Morgan 1992, van Asselt and Rotmans 2002, Ascough Ii, Maier et al. 2008). Generally, three sources of uncertainty have been classified: intrinsic variability in the systems or processes under consideration, uncertainty due to limited knowledge, and decision making uncertainty (Kahneman and Tversky 1982, van Asselt and Rotmans 2002, Ascough Ii, Maier et al. 2008). Variability, known as 'external uncertainty', refers to the unknowable or unpredictable knowledge due to the variability of natural processes and the diversity of social values and human behaviour. The lack of knowledge, known as 'internal uncertainty', refers to the incomplete or imprecise knowledge state about the systems or processes of interest. To take into account decision-making activities, uncertainties occur associated with the selection of a particular decision-making approach, for instance, framing decision problems, quantifying social objectives (usually in monetary term), proposing decision alternatives, assessing decision performance, managing the conflicts and diverse backgrounds of stakeholders, and identifying the preference and risk attitudes of decision makers. Strategically, two approaches will be adopted in light of uncertainty: to *reduce* uncertainty by 'buying information' through integrating existing knowledge and additional research; and to *accept* uncertainty and *act* consciously through selecting robust decisions, design adaptable decision making framework, and take into account decision maker's attitudes towards uncertainty and risk (Thissen and Agusdinata 2008).

Uncertainties due to the intrinsic variability are almost irreducible, while uncertainty due to lack of knowledge can be reduced by additional data collection and further scientific research. Data monitoring and model simulations are the main approaches to gain knowledge and understanding about the past and present conditions, and to forecast future conditions. For example, to estimate climate change impact on water resources, climate models are applied to understand the climate response to social activities and project future hydro-climatic variables. Hydrological models are used to understand the hydrological response to climate change and forecast the future hydrologic states for planning and managing the water systems. Not surprisingly, the limited data availability and the lack of knowledge cause our understanding of the climatic and hydrological behaviour and interactions to be incomplete. This leads to uncertainties incorporated in the modelling process, for example, uncertainty in model structures due to an attempt to form a simplified and approximated expression of a real process, and uncertainty in parameter values and input data due to measurement errors and lack of data. These uncertainties are then propagated and accumulate in the model outputs. Decision makers rely on the information delivered by these model outputs, given these uncertainties, to make decisions in water resource planning and management.

1.3 Robustness and rationality in decision making under uncertainty

Robustness is the key criterion for evaluating alternative decisions under uncertainty (Lempert, Groves et al. 2006). Robust decisions should perform no worse than other decision alternatives over a wide range of plausible future alternatives. The scenario development to describe and quantify uncertainty is crucial to decide the robustness of decisions. In traditional decision analysis, the outcomes of candidate decisions are generated based on the forecasted 'most likely' future scenarios. Since no evidence would fully prove the actuality of the forecasted 'most-likely' futures, decisions based on the 'most-likely' future scenarios would be suboptimal, and different views of 'most-likely' futures are likely to lead to a variety of suboptimal decisions (Kouvelis and Yu 1997). Robustness is opposite to suboptimal; trying to find the decision which performs satisfactorily over all potential assumptions and scenarios about the future. Practically, it is difficult to find a single decision performing no worse than others over all potential scenarios. The final decision should be relatively less sensitive to the assumptions used to characterize the values and probability distributions of the parameters of the decision models.

Rationality has traditionally been assumed to represent the behaviour and preference of decision makers in face of uncertainty, such as Von-Neumann (VNM) rationality (von Neumann and Morgenstern 1947). It implicitly suggests that the behaviour of decision makers can be modelled in mathematical format, and their preference of future actions can be predicted. Rationality has been modelled as maximizing the expected profits in monetary terms. It was challenged by the St. Petersburg Paradox in 1713 which found that individuals refused to invest to play a coin-toss game with infinite expected payoff, noticing that one's satisfaction decreases as marginal payoff increases, and one becomes more cautious with higher payoff while encountering the risk of losing everything. From the engineering perspective, risk is defined as the product of consequence of an event multiplied with its probability of occurrence. However, from the perspective of decision makers, risk is measured as the amount of money that a decision maker is willing to pay to compensate the risk (Levy 1992). For example, some decision makers tend to be cautious to invest in a high-return, high-risk event, while some might be more aggressive and risk-seeking in the same situation. The attitudes of decision makers towards wealth and risk are assumed to influence the decision making result. Von Neumann-Morgenstern modelled rationality as maximizing the expected utility that characterizes the decision makers' satisfaction and attitudes on wealth and the corresponding risks (von Neumann and Morgenstern 1947). Two dimensions are encoded in the expected utility theory: the value by means of utility, and the information by means of probability (North 1968). Rationality in the expected utility framework implies that a rational decision maker values the uncertain outcome of a decision as a linear function of the probabilities (Weijs 2011).

1.4 Research Questions

To establish an integrated decision making framework that explicitly addresses uncertainty, two research objectives are identifies:

(1) How to develop scenarios for future water circumstances to cope with uncertainty?
(2) How to make robust and rational decisions based on the developed scenarios?

Statistics and probability are the traditional tools to deal with uncertainty. Recently, scenario analysis has also been widely employed to explore uncertainty. As a future planning tool, scenarios can be used to explore and articulate the possible future trajectories of the driving forces affecting water resources. Scenarios are defined as plausible and consistent descriptions of future states of the world in face of uncertainty, and each scenario unfolds a possible future (http://www.ipcc-data.org/ddc_definitions.html). Water scenarios have been largely developed and utilized in describing future changes in water resources globally and regionally, in a qualitative and quantitative manner (e.g.,Gallopín and Rijsberman 2000, Rosegrant, Cai et al. 2002, Flörke and Alcamo 2004, Gleick, Cooley et al. 2005). However, two limitations of quantitative scenarios need to be improved: (i) the need for extending discrete scenarios to continuous scenarios to more completely cover future conditions, and (ii) the need for introducing probabilistic scenarios to explicitly quantify uncertainties. Usually, one trajectory was quantified based on each storyline, which omits the possible trajectories between two storylines and constrains the explorative characteristics of scenarios. On the other hand, probabilistic scenarios encourage representing uncertainty and explaining assumptions behind scenarios explicitly (Millett 2008). From a risk analysis perspective, the implementation of probability theory is more approachable for risk quantification and more easily interpreted for risk management (McIntyre, Lees et al. 2003). The assignment of probabilities is subjective to some extent, typically requiring consensus among experts, which can be a difficult and complex process. This has been used to challenge the use of probability distributions in scenario development (Lempert, Groves et al. 2006, Korteling, Dessai et al. 2013). However, although subjective, stochastic approaches provide a transparent and reproducible methodology to systematically quantify probabilities from knowledge or belief of scientists and decision makers. Examples include formal expert elicitation procedures for identifying prior probability distributions (e.g.,Oakley 2010, Low-Choy, James et al. 2012) and Bayesian updating to incorporate new knowledge into the distributions (e.g.,Choy, O'Leary et al. 2009, Scholten, Scheidegger et al. 2013). Furthermore, subjectivity can be reduced (though not completely eliminated) by techniques such as the principle of Maximal Entropy, grounded in information theory, which provides a method for identifying prior probability distributions (e.g. for driving forces) with the largest remaining uncertainty consistent with the available information (Jaynes 1957). Monte Carlo techniques can then be used to propagate uncertainties from the driving forces to the variables of interest (Dessai and van der Sluijs 2011). Therefore, the first contribution of this work is to address limitations in existing approaches by advancing scenarios from discrete to continuous, and from equal-likelihood to probabilistic ensembles to explore uncertain futures.

The developed scenarios are critical to support decision making under uncertainty. The application of the range of continuous and probabilistic scenarios allows the search for robust decisions. The second contribution of this work consists of identifying decision alternatives, not on the basis of any single or several 'most-likely' scenarios, but instead on the basis of the full probability distributions of the quantified scenarios. A risk profile is applied to represent the outcomes of decision alternatives and the corresponding cumulative probability distributions. The full probability distribution view that the risk profile provides is more informative for the decision maker in hedging against the risk of poor performance for some scenarios than in the expected performance over all potential scenarios (Kouvelis and Yu 1997). The outcomes of decision alternatives are represented using monetary terms based on economic models, but also utility terms from utility functions to incorporate decision makers with risk averse, risk neutral and risk seeking attitudes towards the monetary outcomes. The expected utility theory framework is used to support decision-making by maximizing the expected utility of the decision alternatives. It provides normative and descriptive methods for rational decision making on the basis of explicit probabilistic information to characterize uncertainty. This is in contrast with actual human behaviour, which often is not rational and typically violates expected utility theory (Shaw and Woodward 2008). Finally, to account for subjective assumptions made in the modelling process, a sensitivity analysis was applied to test the sensitivity of decision performance when assumptions of probability distributions and values of the decision models change. The work thus builds and applies a probabilistic scenario-based decision making framework to incorporate uncertainty analysis and support robust and rational decision making in a risky context, and extends both the classical decision making framework focusing only on the most-likely scenarios and the traditional scenario planning and robust decision making frameworks that exclude probabilistic information.

1.5 Outline of the thesis

Scenarios are critical to deal with uncertainty for decision making in water resource planning and management. Chapter 2 reviews scenario development techniques and studies for a better understanding of the knowledge of scenario development. The chapter identifies two major limitations of quantitative scenario development studies, and proposes a probabilistic framework to advance scenario development.

Chapter 3 develops probabilistic climate scenarios (precipitation and temperature) based on the projections of GCMs, and applies them as inputs to a conceptual hydrological model to construct probabilistic scenarios of water availability in the Yellow River Basin (YRB), China.

Chapter 4 develops probabilistic scenarios of future water demand in the YRD, China. An existing expert elicitation technique, i.e. the SHELF method, is used to elicit prior probabilities of socio-economic driving variables from local experts. Probability distributions from individual experts are then aggregated, and correlations between different variables are accounted for by using a multivariate probability distribution based on the Gaussian Copula.

Chapter 5 reviews existing decision making frameworks and decision rules under uncertainty applied in water resources planning and management. A probabilistic scenario-based decision making framework is proposed to handle uncertainties and support decision making in a systematic, robust and rational manner. The framework relies on a full probabilistic range of scenarios, and ranks decision alternatives based on expected utility theory.

Chapter 6 applies the developed decision making framework to demonstrate the decision making process under uncertainty in the YRD, China. The decision problem focuses on matching water supply with water demand using management measures for long-term water planning. Monetary and utility-based objective functions are used to evaluate decisions by combining the engineering as well as decision makers' perspectives. Probabilistic scenarios of future water supply and demand are analysed, and stochastic utility based decision rules are used to rank decision alternatives, taking into account different risk tolerance levels of decision makers. The chapter ends with sensitivity analysis to test the robustness of the final decision with respect to various assumptions made.

Chapter 7 reports conclusions, and proposes recommendations for further research on decision making under uncertainty for water resources planning and management.

Chapter 2 Scenario development for water resources planning and management

2.1 Introduction

Scenarios have been used as an important tool for exploring future uncertainties in a coherent, consistent and plausible way, and as such, they have been widely used for strategic planning and policy making (Yoe 2004). In addition, scenario-based planning has been adopted as a management technology to articulate mental models about the future and to help managers make better decisions (Martelli 2001).

Scenarios were first used by strategic planners for the U.S. military to forecast possible consequences of a nuclear war after World War II. Herman Kahn, regarded as the 'Father of scenario planning', introduced scenario planning as a method to think about uncertain futures and for generating ideas and strategies in business planning (Kahn 1962). Since then, scenarios have been used in a wide range of applications, with subtle differences in how scenarios were defined, depending on the context or field of application. For example, Porter (1985) defined a scenario as 'an internally consistent view of what the future might turn out to be- not a forecast, but one possible future outcome'. Schwartz (1991) interpreted scenarios as 'a tool for ordering one's perception about alternative future environments in which one's decisions might be played out'. The Intergovernmental Panel on Climate Change (IPCC) described a scenario as 'a coherent, internally consistent and plausible description of a possible future state of the world. It is not a forecast; rather, each scenario is one alternative image of how the future can unfold.' (http://www.ipcc-data.org/ddc_definitions.html). The key point in all these definitions is that scenarios deal with uncertainty in the future, but that they are different from forecasts or predictions. Indeed, the aim of scenario planning is to generate a wide range of possible futures, rather than focusing only on the most likely outcome.

Several reviews of scenario planning have appeared in the literature. Chermack et al. (2001) reviewed scenario planning literature from a conceptual perspective, describing the status of knowledge on scenario planning. Yoe (2004) reviewed literature on scenario planning for decision-making under uncertainty, and outlined specific models and techniques to develop

This Chapter is based on "Scenario development for water resource planning and management: A review", C. Dong, G. Schoups, N. van de Giesen, Technological Forecasting & Social Change, 2012.

scenarios. Wagner et al. (2006) provided a review of the state-of-the-art of scenario development and proposed a formal framework for scenario development. Börjeson et al. (2006) categorized scenarios into three types, namely predictive, explorative and normative, and discussed techniques for scenario development appropriate for each category.

In an extensive overview of scenario development techniques, Bishop et al. (2007) inventoried eight categories of techniques, including a total of 23 variations, and discussed their utility, strengths and weaknesses. Varum and Melo (2010) provided a systematic overview of scenario planning studies published in the last few decades. Recently, Haasnoot and Middelkoop (2012) reviewed water policy evolution by using scenarios in the Netherlands, documenting a shift from predicting to exploring the future, which has resulted in more robust decision-making.

Previous studies on water resource management have demonstrated that scenarios are also useful to account for uncertainties associated with climatic, demographic, economic, social, technical and political conditions that affect the performance of water resource systems, including their effects on future water availability, water demand and water management strategies (e.g.,Gallopín and Rijsberman 2000, Alcamo and Gallopín 2009). Scenario-based approaches have been applied to explore and analyze future water-related issues, as well as to support water managers and decision-makers to put forward solutions for potential problems (Mahmoud 2008).

Although a number of studies, as outlined above, have focused on reviewing and summarizing the philosophy and practice of scenario planning, a review specifically aimed at water resource planning and management is missing. Therefore, as the number of studies on scenario-based water resource planning and management is booming, the goals of this paper are to review the status of knowledge on scenario development for water resource planning and management, to highlight the shortcomings in existing methods, and to suggest potential opportunities for improving development of water resource scenarios.

The chapter is structured as follows. We start in section 2.2 by formulating typical water management goals, and identifying the main uncertainties and driving forces that need to be taken into account. Several examples from the literature are given to illustrate the diverse range of water planning practice. In section 2.3, we outline a general procedure for scenario development, consisting of all the important steps that ideally should be included in water resource scenario development. Section 2.4 reviews how these steps have been implemented in existing studies.

Section 2.5 highlights aspects of the general procedure that have not been adequately addressed in existing literature, leading us to suggest a methodological framework in section 2.6 that can potentially address these limitations.

2.2 Water resources planning and management under uncertainty

The fundamental goal of water resource planning and management is to match the demand for water by the socio-economic system with the supply (quantity and quality) of the water system through administrative control and management (water regulations/laws and infrastructure), without compromising ecosystem sustainability (GWP 2000). Figure 2.1 and Table 2.1 give an overview of the variables and interdependent subsystems that need to be taken into account in this context. In essence, changes in water resource systems (W) are driven by changes in three related subsystems, i.e. the climate system (C), the socio-economic system (SE) and the management system (M). Important socio-economic variables include population growth, economic development, technological change, and water and land use practices. For example, demographic change, economic development, technological innovation and geographical conditions directly impact future water consumption patterns, and water demand by different users (McCarthy, Canziani et al. 2001). The climate system has a direct impact on water availability and water demand via changes in temperature, precipitation and evaporation. Finally, management intervention such as water allocation strategies, legislative standards, and political intervention stimulates changes in the socio-economic system and hence plays an important role in influencing future pathways of water systems.

Uncertainty about the future development of the socio-economic and climate systems is the main reason for developing water resource scenarios. For instance, with the growth of population and economy, water demand from domestic, industrial and agricultural sectors will increase, resulting in more stress on limited, shared water resources. Anthropogenic climate change, caused by Greenhouse Gas (GHG) emissions, with higher temperature and altered precipitation patterns, directly impact water resource availability and irrigation water demand (McCarthy, Canziani et al. 2001, Fischer, Tubiello et al. 2007, Chung, Rodri´Guez-di´az et al. 2010, Falloon and Betts 2010, Xiong, Holman et al. 2010, Zhu and Ringler 2012), as well as water quality and ecosystem stability. Assessing future impacts of climate change is subject to significant uncertainty, due to knowledge and data gaps on climate system behavior and its interaction with the water system. This is reflected in widely diverging model-based projections of future precipitation and water supply (Gay and Estrada 2009, Buytaert, Vuille et al. 2010, Chung, Rodri´Guez-di´az et al. 2010, Falloon and Betts 2010). Consequently, mitigating future potential negative impacts of climate change on water resources has become an important challenge to water managers (IPCC 2007).

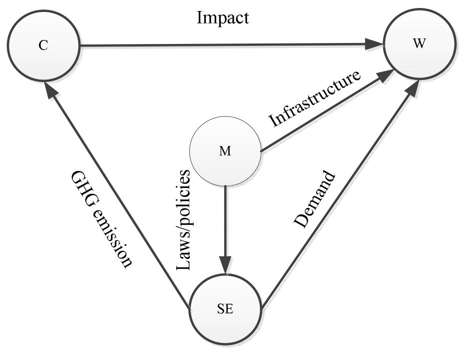


Figure 2.1 Relationship between three interdependent systems: the climate system (C) and socio-economic system (SE) are the main drivers affecting change in water systems (W). Water resources management (M) is used to achieve a sustainable balance between water demand (via its influence on SE, e.g. through land and water use policies) and water supply (via its effect on W, e.g. by infrastructural investments to distribute water). Examples of key variables in each system are listed in Table 2.1.

Table 2.1 Main driving forces and variables from three interdependent systems that impact water systems

Interdependent systems	Main driving forces	Variables
Socio-economic system	Demographic change	population, food or lifestyle, migration,…
	Economic development	GDP level, industry structure…
	Technological innovation	pollution control, wastewater treatment, improvement in water use efficiency …
	Geographical conditions	land use, vegetation cover, irrigation area…
Climate system	Climate change	temperature, precipitation, humidity, wind speed,…
Management system	Management measures	water infrastructure investment ,water transfer…
	Legislative standards	water-use quota, water allocation, water regulations…
	Political intervention	water policies, water prices …

To cope with these significant uncertainties in water resource planning and management, several studies have focused on developing scenarios for water systems. The underlying idea is that scenarios that display alternative future states of the water system facilitate water managers to make robust decisions and management strategies (Lempert, Popper et al. 2003, Lempert, Groves et al. 2006). Scenario development for water resources planning and management help decision makers to understand the implications of the uncertainty (Groves 2006) and explore the future water availability (surface water, groundwater storage, water quality) (Mimikou, Baltas et al. 2000, Mahmoud, Gupta et al. 2011, Zhovtonog, Hoffmann et al. 2011) and water demand conditions (Flörke and Alcamo 2004, Zhu and Ringler 2012), and as a result, designing and making robust management strategies or policies to achieve planning objectives (alleviating water stress, improving water quality, maintaining the ecosystem service, etc.) (Lévite, Sally et al. 2003, Muhammetoglu, Muhammetoglu et al. 2005, Groves 2006, Weng, Huang et al. 2010).

Table 2.2 lists several illustrative examples of scenario development for water resources management across a range of scales. Projects such as the World Water Vision (WWV) (Cosgrove and Rijsberman 2000, Gallopín and Rijsberman 2000) , the Global Water Outlook (GWO) (Rosegrant, Cai et al. 2002), and Global Water Futures (GWF) (Alcamo and Gallopín 2009, Gallopín 2012) focused on assessing water availability and demand at the global scale, with subsequent downscaling to continental and national scales to provide a reference for regional water resource planning and management. The Millennium Ecosystem Assessment (MA) explored four different scenarios for managing ecosystem services in the face of growing water demand, considering biodiversity and human-being welfare (Carpenter, Pingali et al. 2005). Water footprint scenarios for 2050 analysed global and European consumptive green, blue and grey water footprint (Hoekstra, Chapagain et al. 2011) under four storylines (global/regional market/sustainability) (Ercin and Hoekstra 2012). Three water utopias were created from the perspectives of hierarchist, egalitarian and individualist (Hoekstra 2000) to assess long-term future water situations in Zambezi basin (Hoekstra 1998). At the European scale, the SCENES project (Water Scenarios for Europe and for Neighbouring States) developed a set of comprehensive scenarios of Europe's future freshwater resources to address how water resources in Europe may develop up to 2050 (e.g.,Iital, Voronova et al. 2011, Zhovtonog, Hoffmann et al. 2011). The European Outlook on Water Use proposed by the European Environment Agency (EEA) presented quantitative scenarios for future water use, water availability and water stress up to 2030 in 30 European countries, including recommendations for improving water outlooks in Europe (Flörke and Alcamo 2004). Many examples also exist of regional-scale scenario development. For example, a study in central Greece considered two climate scenarios causing decreases in stream flow and water quality (Mimikou, Baltas et al. 2000), and other studies e.g. in the Verde River Watershed and the San Pedro basin in Arizona (Mahmoud 2008, Mahmoud, Gupta et al. 2011), and in California (Groves 2006), have looked at matching water supply and demand under a range of future climate, demographic, and economic scenarios. Scenarios for driving forces have also been used to evaluate effectiveness of mitigation strategies (Carter, Jones et al. 2007). For example, water pricing has been explored to stimulate more efficient water use, and redistribution of water from domestic and industrial sectors to irrigation and environment

(Rosegrant, Cai et al. 2002). Finally, a set of emission scenarios has been developed by the Intergovernmental Panel on Climate Change (IPCC), considering future anthropogenic greenhouse gas (GHG) emissions and climate change, as a function of demographic, economic, and technological changes, land-use patterns, and various other human activities (Nakicenovic, Alcamo et al. 2000). Although the IPCC scenarios are not listed in the table as they are not directly water scenarios, they are highly important due to their wide usage in estimating climate change impact on water resources (Arnell 2004, Fischer, Tubiello et al. 2007, Charlton and Arnell 2011, Zhu and Ringler 2012).

Table 2.2 Examples of scenario development at global, continental, and regional scales for water resources management

Name of study	Time horizon	Spatial scale	Main variables included in scenarios				Story -line no.	Source
			W	C	SE	M		
WWV	2025	Global	water availability and demand	none	population, GDP, etc	none	3	(Cosgrove and Rijsberman 2000, Gallopín and Rijsberman 2000)
GWO	2025	Global	water availability and demand	precipitation, temperature	population, GDP, etc	infrastructure investment	3	(Rosegrant, Cai et al. 2002)
GWF	2050	Global	water withdraw	extreme climate events	birth/death rate, GDP, water use efficiency, etc.	water transfer	5	(Gallopín 2012)
MA	2015/ 2030/ 2050	Global	water availability and use, aquatic biodiversity	precipitation, temperature	population, GDP, water use efficiency, land use, etc.	none	4	(Carpenter, Pingali et al. 2005)
Water footprint (WF) scenarios	2050	Global/ Europe	water footprint	none	Population, economy, production pattern, consumption pattern, technology	none	4	(Ercin and Hoekstra 2012)
Three water utopias	2050	Zambezi	water supply/deman d	none	Population, economy, cropland, hydropower, technology	water trade, wastewater treatment	3	(Hoekstra 1998)
SCENES	2050	Europe	water availability and demand	precipitation, temperature	population, GDP, irrigation area, land use, etc.	European /national policies and legislation	4	(Iital, Voronova et al. 2011, Zhovtonog, Hoffmann et al. 2011)
European Outlook on Water Use	2030	Europe	water demand	precipitation, temperature	population, GDP, electricity production, irrigated areas, etc.	none	2	(Flörke and Alcamo 2004)
Pinios river basin	2050	Greece	water availability and water quality	precipitation, temperature	contaminant concentrations	none	2	(Mimikou, Baltas et al. 2000)
Verde River Watershed	50 years	USA	water availability and water demand	precipitation, temperature	population, GDP, irrigation efficiency, land use	water demand allocation	8	(Mahmoud, Gupta et al. 2011)
SAHRA Scenarios	2030 /2050	USA	water demand, groundwater level	precipitation, temperature, wind speed …	population, water use intensity, land use, water-saving appliances etc.	water rights, legislation	8	(Mahmoud 2008)
California water demand	50 years	USA	water demand	none	population, water use intensity and coefficients, etc.	none	4	(Groves 2006)
World water and food	2025	Global	water withdrawal	precipitation, temperature	population, irrigation area, water use intensity and efficiency, etc.	water price, irrigation investment	4	(Rosegrant, Cai et al. 2002)

2.3 General procedure for water resources scenario development

As illustrated in the previous section, scenarios have been developed for a wide variety of settings, scales, and geographic settings. Despite this variety, most studies follow one or more steps of the general iterative procedure outlined in Figure 2.2. The various steps can be summarized as follows:

(1) Define focal questions (water-related variables), main driving forces (variables), and identify main sources of uncertainty. This step includes understanding the current situation, and finding out focal questions and objectives relevant to water managers and stakeholders. It is crucial to identify key variables representing the focal question and driving forces (*SE*, *C*, and *M* systems) as well as the main uncertainties affecting the stakeholders' objectives. Additionally, appropriate temporal (daily, monthly, seasonal, annual, decadal) and spatial (local, regional, basin, continental, global) scales need to be identified in the analysis.

(2) Construct scenario logic and write down stories. Given the key variables and driving forces identified in step 1, the goal is to qualitatively describe a small number of scenarios that essentially map out the boundaries of what the future may bring. These storylines focus on the driving forces impacting the water system and should provide a broad view of future change, in response to the situation when the future is driven by forces laying outside the control and foresight of decision makers (Gleick, Cooley et al. 2005). To write down the storylines is then to fill in the details (especially focusing on the driving forces) of the scenario logic defined.

(3) Quantify future development of driving forces according to the storylines. This step involves assigning numerical values and associated probabilities to the driving forces based on their development described by the storylines. For example, future changes in population growth rate, irrigation area, and temperature are quantified.

(4) Quantify future development of water-related variables of interest. In this step, quantitative scenarios for the driving forces are translated into corresponding quantitative scenarios for water-related variables, typically using computer simulation models.

(5) Refine and update the scenarios. Scenario refinement is an iterative process aimed at achieving consistency between quantitative and qualitative results obtained during all the

previous steps. An additional layer of revision is provided by updating the scenarios as new knowledge and data become available. This step acknowledges that scenario development is not a ‘once-for-all’ activity, but rather an evolving and continuing learning process.

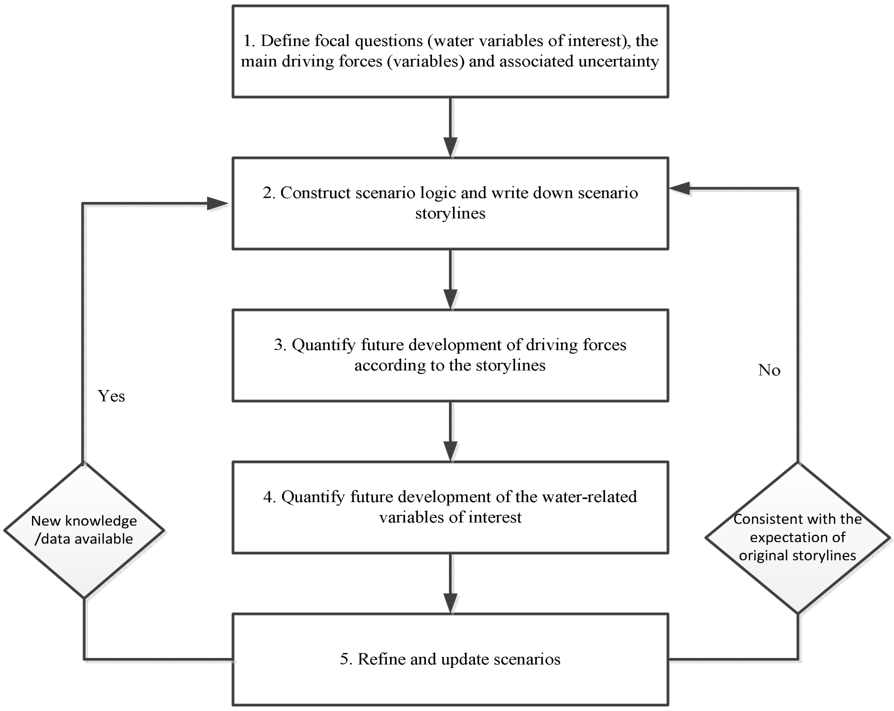


Figure 2.2 General iterative procedures for water resources scenario development.

We note that the procedure outlined above, and in Figure 2.2, combines qualitative and quantitative scenario construction. Although scenarios were originally conceived as qualitative stories by Kahn (1962), and Schwartz (1991), modern scenario analysis often relies on computer models to quantify future change (Groves 2006, Alcamo 2008). Qualitative scenarios, in most cases, describe futures in the form of storylines, which helps the communication and understanding between scientists, decision-makers and stakeholders with different knowledge levels. However, the lack of numerical information hampers further scientific and decision-making activities. For example, when a reservoir has to be designed in order to alleviate the unevenly distributed water resources, storylines to describe water shortage situations in dry years and water abundance in wet years are not sufficient to identify an optimal design for the reservoir.

Examples of qualitative-quantitative scenarios have been provided for exploring global future water situations in the framework of the World Water Vision, the Global Environmental Outlook, and the IPCC emission scenarios (Cosgrove and Rijsberman 2000, Nakicenovic, Alcamo et al.

2000, UNEP 2002). For regional/local water resources planning, a number of qualitative-quantitative scenarios were developed to analyze future water quantity (Doll 2004, Flörke and Alcamo 2004, Beck and Bernauer 2010, Zhu and Ringler 2012) and water quality (e.g.,Vaché, Eilers et al. 2002, King, Brown et al. 2003, Ames, Neilson et al. 2005), as well as to peruse sustainable ecosystems (e.g.,UNEP 2002, Carpenter, Pingali et al. 2005, UNEP 2007).

2.4 Current implementation of scenario development steps

In this section, we evaluate how the different steps in the general procedure of Figure 2.2 have been implemented in existing studies. Each of the five main steps is discussed in sequence.

2.4.1 Step 1 - Define focal questions and main driving forces, and identify main sources of uncertainty

Expert judgment and stakeholder involvement have been widely applied for identifying the main driving forces, variables of interest, and sources of uncertainty in particular case studies (Gallopín and Rijsberman 2000, Rosegrant, Cai et al. 2002, Mahmoud 2008, Mahmoud, Gupta et al. 2011). A scenario team or panel consisting of experts and stakeholders is established at the onset of the process (Alcamo 2008), allowing extensive communication and cooperation among team members.

Expert judgment was first adopted by Herman Kahn, and was referred to as 'Genius forecasting' (Bishop, Hines et al. 2007). It relies on expert knowledge, reasoning, experience, imagination, and even intuition. Indeed, expert judgment has played an important role in the scenario definition process in cases where process knowledge is limited, data is scarce, and uncertainty is large. In those cases, their scientific knowledge and experience helps to identify and integrate representative variables from the major driving forces to the focal problems. Several formal procedures have been developed and applied to streamline this process, including surveys, interviews, Delphi techniques, nominal groups and brainstorming (Huss and Honton 1987, Rikkonen, Kaivo-oja et al. 2006).

This process may be further expanded by inviting stakeholders to participate in the development process and have them share their opinions and local knowledge. Stakeholder-driven judgment is an open process involving stakeholders, researchers and decision-makers, to think, communicate and write down possible futures. The identification and choice of stakeholders are critical for the quality of scenarios, due to their large influence on the identification of key driving forces and the formation of scenario outlines. They are usually selected from groups with different interests and requirements, and may comprise of local experts, governmental officials, and representatives of social groups or local residents. Stakeholders are invited to workshops, and are encouraged to discuss key driving forces and uncertainties of socio-economic, environmental and administrative aspects, while researchers assist them by providing scientific information. Qualitative participatory methods make use of pictures, card-techniques, collages, rich pictures and time lines to help stakeholders imagine and brainstorm the driving forces and main uncertainties (Van Vliet, Kok et al. 2007).

2.4.2 Step 2 – Construct scenario logics and write down storylines for driving forces (*C, SE*)

Both expert and stakeholder-driven judgement play a fundamental role in constructing scenario storylines. For example, scenario storylines for the IPCC-SRES and MA were developed based on knowledge and judgment of a wide range of experts from climate, hydrological, environmental, social and economic sciences. Regional stakeholder-driven scenarios were elicited in the SCENES and SAHRA projects (Table 2.2). A stakeholder discussion panel was built and required to work on a scenario definition exercise, after which storylines of scenarios were constructed for regional water resources development (Mahmoud 2008).

Development of scenario logics is further facilitated by techniques such as dimensions of uncertainty analysis (Bishop, Hines et al. 2007) and global business network (GBN) matrix analysis (Schwartz 1991). The GBN matrix is a two-dimensional matrix comprising of two critical uncertainties with two states assigned to each uncertainty dimension. The process thus results in a total of four scenarios, which are subsequently further elaborated (storyline development). To construct the matrix, the two most critical uncertainties need to be selected, and extreme states are assigned to the two critical uncertainties to cover a wide range of plausible futures. This two-dimensional approach has been adopted to develop the widely-used IPCC-SRES scenarios (A1, A2, B1, B2 storylines) (Nakicenovic, Alcamo et al. 2000), which consist of two uncertainty dimensions (global/ regional, economy/ environment-oriented) to describe future changes in population, economy, governance and technology. Similarly, four scenarios were created for MA using this technique, with two uncertainty dimensions defined by global/regional development and pro-active/reactive attitudes towards the environment (Carpenter, Pingali et al. 2005). The GBN matrix can be used several times or by several groups in order to enrich the future alternatives. The SAHRA team defined two uncertainty dimensions (variable climate/sustained drought, declining monitoring/enhanced monitoring), and invited two stakeholder groups to fill in each uncertainty domain. Thus, the two groups constructed eight storylines by combining the GBN matrix (Mahmoud 2008).

Obviously, the idea behind the GBN matrix can be extended to more than two uncertainty dimensions, resulting in what could be called the Expanded GBN matrix, which in theory has no limitation on the number of uncertainties or the number of alternative states for each uncertainty. For example, three uncertainty dimensions corresponding to climate change, demographics and economic development were identified in the Verde River Watershed study (Table 2.2). Together with two extreme states for each uncertainty dimension, this resulted in 8 scenarios for future water supply and demand over a 50-year planning horizon (Mahmoud, Liu et al. 2009). However, with the increasing number of uncertainty dimensions, the complexity of these techniques hampers more widespread usage (Bishop, Hines et al. 2007).

A common practice is to include a ‘Business-as-usual’ scenario, in combination with one or two extreme scenarios (Cosgrove and Rijsberman 2000, Gallopín and Rijsberman 2000, Groves 2006). The ‘Business-as-usual’ (BAU) scenario, also named as ‘without-project conditions’ by the U.S. Army Corps of Engineers (Yoe 2004), is the future without any specific action or intervention taken to alter the future path. The World Water Vision group explained ‘Business-as-usual’ (BAU) scenario as a description of a world in which current policies on water resources management and development are continued unchanged, while the other two storylines ‘Technology, Economics& the Private Sector’ and ‘Values and Lifestyles’ included the optimistic view of improving water management and pessimistic view of a future water crisis respectively (Gallopín and Rijsberman 2000). For the European outlook on water use, a BAU scenario was developed assuming that current environmental policies continue, and no specific policies are implemented to curtail water use. This scenario was compared with a climate scenario based on GHG emission reduction policies (Flörke and Alcamo 2004).

2.4.3 Step 3 - Quantify future development of driving forces (*C*, *SE*) according to the storyline

Most studies rely on expert judgment and modelling to convert qualitative scenario descriptions into quantitative scenarios. The process typically involves generating a quantitative scenario (with numerical values attached to the relevant variables) for each of the qualitative storylines developed in step 2. The most common assumption is then that the various scenarios are all equally likely. As an example of the use of expert judgment, the SCENES team employed fuzzy cognitive mapping (FCM), which is a semi-quantitative method that allows conversion of qualitative expert judgment into quantitative scenarios (Kok and van Vliet 2011). Cognitive maps were first introduced by Axelrod (1976) in social science, and fuzzy logic was added to the cognitive maps by Kosko (1986) to quantify ambiguity and relations among uncertain variables. Hence, the method generates quantitative scenarios with an estimation of the associated uncertainty.

More traditional modelling approaches differ between socio-economic and climate variables. A common approach for assessing socio-economic change under a 'Business-as-usual' scenario is to perform trend analysis, whereby historical trends in e.g. population growth are simply extrapolated (Bishop, Hines et al. 2007). In other cases, one may rely on results from more extensive socio-economic analyses; for example, numerical values for population growth in the IPCC-SRES and MA scenarios were taken from previous studies of the United Nations and International Institute for Applied Systems Analysis (Carpenter, Pingali et al. 2005, IPCC 2007, Alcamo 2008).

The most common approach for quantifying future climate variables such as precipitation and temperature is to post-process the output from General Circulation Models (GCMs) driven by the IPCC emission scenarios (Mimikou, Baltas et al. 2000, Eckhardt and Ulbrich 2003, Buytaert, Vuille et al. 2010, Chung, Rodri´Guez-di´az et al. 2010). GCMs represent and simulate physical processes in the atmosphere, ocean, cryosphere and land surface. Output from more than 20 GCMs is now available for generating monthly climate scenarios up to the year 2100. The GCM outputs are global, and downscaling techniques are typically used to obtain regional climate scenarios (e.g.,Ramirez and Jarvis 2010). Often only a small number of GCMs are considered to generate scenarios (e.g.,Mimikou, Baltas et al. 2000, Eckhardt and Ulbrich 2003, Chung, Rodri´Guez-di´az et al. 2010). More recently, however, studies tend to generate climate scenarios by combining many GCMs and emission scenarios (e.g.,Dessai and Hulme 2007, Buytaert, Vuille et al. 2010), thereby more accurately representing the uncertainties associated with the emission scenarios driving these models, as well as the inherent uncertainties of modelling the complex climate system. Guidelines for selecting and combining GCM results to help scientists and managers based on perceptions of model evaluations were proposed. Projections of the most sensitive climate variables to the decision problem are suggested to combine as many different models and emissions scenarios as possible. Effort should be made to evaluate the defined variables against observations just to recognize model biases instead of weighting and discarding the model outputs, and to understand the uncertainty of downscaled regional climate projections instead of ignoring them in the decision-making process (Mote, Duffy et al. 2011).

2.4.4 Step 4 - Quantify future development for water-related variables (*W*)

Once quantitative scenarios have been constructed for the relevant socio-economic (*SE*) and climate (*C*) driving variables, these are translated into corresponding quantitative scenarios for water-related variables (*W*), such as water availability and demand. Computer simulations have typically been used in this step, based on either deterministic or probabilistic models.

Deterministic hydrological models are often used to simulate scenarios of future water availability, water demand and water quality, taking the projections of climatic variables and socio-economic variables as model input (Arnell 1999, Arnell 2004, Chung, Rodri´Guez-di´az et al. 2010). Hydrological rainfall-runoff models have been applied both globally and regionally to project future water availability scenarios, by assessing the impact of climate change on water resources based on the climatic scenarios generated by GCMs (Arnell 1999, Liuzzo, Noto et al. 2010). Water demand-oriented models have been used to analyse and visualize scenarios of future water supply-demand (e.g.,Beck and Bernauer 2010, Mahmoud, Gupta et al. 2011). Examples are the well-known water supply-demand models like the WaterGAP model (Flörke and Alcamo 2004), the IMPACT-WATER model (Rosegrant, Cai et al. 2002), and the SWAT model (Soil and Water Assessment Tool) (Vaché, Eilers et al. 2002, Eckhardt and Ulbrich 2003, Jayakrishnan, Srinivasan et al. 2005).

A shortcoming of these models is that they do not account for inherent uncertainties in the models themselves. Probabilistic models have been used to circumvent this limitation. For example, Bayesian Networks have been used to generate water quality, water quantity or related environmental scenarios with probabilities under different management strategies or policies, thereby helping to test the robustness of alternative management options (Ames, Neilson et al. 2005, Castelletti and Soncini-Sessa 2007). For computational reasons, these applications typically resort to discretization of the relevant variables. An alternative class of probabilistic method relies on scenario trees. A scenario tree aggregates predefined scenarios into a tree structure, e.g. representing a multi-period future time horizon. Due to their flexibility in defining scenarios dynamically, scenario trees are commonly used in multi-stage stochastic decision making in water management. Particularly in water supply and water allocation problems, scenario trees are used to represent uncertainty of the unknown parameters or inputs of multi-stage stochastic programming models (Watkins Jr, McKinney et al. 2000, Jayakrishnan, Srinivasan et al. 2005).

2.4.5 Step 5 – Refining and updating scenarios

Scenario refinement can be implemented through an iterative process, whereby quantitative model output is communicated back to the larger group of experts and stakeholders involved in the initial qualitative scenario development phase. An example where this has been done and documented is the 'Story-and-Simulation' approach developed by the SCENES project, which converts qualitative storylines and quantitative scenarios iteratively (Van Vliet, Kok et al. 2007, Alcamo 2008, Kok, van Vliet et al. 2011). Outlines of scenarios proposed by a scenario team involving stakeholders and quantitative water scenarios simulated by a modeling team have to be reported to an expert panel in order to revise the storylines and check the consistency between qualitative descriptions and quantitative outcomes. The process of rewriting the storylines, re-assigning values to the driving forces and re-quantifying the scenarios if necessary is iterated until an accepted version of the storylines and quantification is reached.

Further, as the future will not stop changing, updating scenarios iteratively by periodic review and corrections, incorporating new knowledge and data as they become available, is a useful step, as Schwartz (1991) stated 'it is important to know as soon as possible which of several scenarios is closest to the course of history as it unfolds'. Post-audits and monitoring have been used for this purpose, e.g. in the formal framework for scenario development for the water supply and demand scenarios in the Verde River Watershed, USA (Table 2.2). Post-auditing allows one to re-examine and refine scenarios such that scenarios account for the most recent information. Monitoring establishes measurable indicators to find which scenarios are converging or diverging from the actual evolving future, in order to improve the consistency of observed and designed scenario paths in an on-going scenario development process. Use of such indicators allows one to evaluate the success of the intended scenario development goals, and to update if needed (Liu, Mahmoud et al. 2008). A similar process was used to adaptively revise the IPCC GHG emission scenarios, which are widely used to quantify the impacts of future climate change on water resources. So far, IPCC has updated the scenarios twice since 1990 (SA90, IS92 and SRES) (IPCC 1990, IPCC 1992c, IPCC 2000), and new emission scenarios are anticipated for the Fifth Assessment Report in 2014 (IPCC 2008). Changes over the three scenarios were reviewed and evaluated according to these five aspects: the description of storylines, structure, development process, scientific setting and triggers, and applicability. Significant enhancement has been achieved in the scientific adequacy (credibility), transparency, participation (legitimacy) (Hulme and Dessai 2008), and applicability of the IPCC's emission scenarios (Girod, Wiek et al. 2009).

2.5 Limitation in existing applications

Three limitations in current applications are highlighted, namely (i) the limited number of quantitative scenarios considered, (ii) implicit and incomplete characterization of uncertainties, and (iii) the lack of transparency when implementing expert judgment procedures.

2.5.1 Limited number of quantitative scenarios

As documented in Table 2.2, all the reviewed studies only considered a handful of discrete quantitative scenarios, which are essentially obtained by assigning numerical values to variables in the corresponding qualitative storylines. Whereas qualitative scenarios have been limited to a handful of descriptive storylines or themes, mostly including a 'Business-as-usual' scenario and a couple of extreme scenarios along several axes of main uncertainties, quantitative scenarios should ideally also cover intermediate situations in between these storyline descriptions. Indeed, the key variables in water resources planning are almost always continuous; they are not restricted to a discrete set of values. Hence, artificially restricting the scenario space to a discrete set provides only a very crude approximation of physical states of climate/water-related variables. In other words, quantitative scenarios should not only assign values discretely based on the main qualitative scenario themes, but also for a multitude of intermediate situations. The wide range of continuous quantitative scenarios are useful to test and evaluate the robustness of management strategies against all the future states included (Tezuka, Murata et al. 2005, Groves 2006). The implementation of statistical tools and mathematical algorithms together with the increased computational capabilities facilitate the generation and utilization of the large set of scenarios. For example, Mont Carlo applications routinely involve millions of model runs, where each model run essentially represents a different scenario (Tezuka, Murata et al. 2005). Scenario discovery algorithms classify a wide range of scenarios simulated by hundreds to millions of model runs into multi-dimensional regions, and select regions of interest reflecting the performance of policies for decision-support application (Bryant and Lempert 2010). In order to design robust strategies to narrow the water supply-demand gap in California up to 2030, 500 different future states of water supply and demand were sampled from a large set of plausible future states to evaluate 24 New Supply/ Efficiency Signpost policies by using scenario discovery algorithms (Groves 2006).

2.5.2 Implicit and incomplete uncertainty characterization

Existing applications typically consider scenarios to be equally likely. Exceptions are studies that develop probabilistic scenarios using Bayesian Networks (Ames, Neilson et al. 2005, Castelletti and Soncini-Sessa 2007). A potential drawback of using scenarios without explicitly stating their probabilities is that this may lead to confusion, as scenario users would assign probabilities themselves or select scenarios intuitively (Schneider 2001). For climate scenarios, Gay (Gay and Estrada 2009) states that there is a danger that missing probabilities would free up decision-makers to take any action given the high level of uncertainty surrounding the climate change threat. The same case could occur to decision makers when no probability or equal probability is attached to water scenarios. By attaching probabilities to the various scenarios, the weight that each scenario plays in developing water management plans is explicitly considered and quantified. Realizing that the objective scenario probabilities in the classic frequentists' sense are impossible to obtain (van de Heijden 1994), the probabilistic assessment is necessarily subjective so that it is consistent with available knowledge and expert judgement (Gay and Estrada 2009). It is also extremely useful as long as it is done in a transparent and explicit manner. Several axiom-based theories are available to check and limit the subjectivity. The use of Bayesian probabilities drives people to explain the judgements explicitly and they are open to peer review and criticism, thereby exposing hidden assumptions, biases, and expectations behind the purely intuitive scenarios (Millett 2008). The Maximum Entropy framework allows the least prejudiced probability assignment in the sense that it utilizes all the information available but remains as non-committal as possible when information is not available (Jaynes 1957, Myung, Ramamoorti et al. 1996, Weijs, Schoups et al. 2010). In addition, focusing exclusively on uncertainty in driving variables (climate and socio-economic) and ignoring other uncertainties such as uncertainties introduced by the various model components used to generate scenarios for water-related variables, should be addressed to avoid overconfidence in the model outputs. For instance, a probabilistic framework was formulated to generate low-flow scenarios under climate change impact for the river Thames, including the consideration of uncertainties from hydrological models by weighting their performance of reproducing the historical annual low flow series.

2.5.3 Lack of transparency

A recurring finding in reviewed literature is the lack of clarity and transparency as to how descriptive storylines are converted into quantitative scenarios. A way to increase the transparency is to build specific protocols in the scenario development team or panel, such as the protocol for converting qualitative to quantitative knowledge designed in the 'Story-and-Simulation' approach (Alcamo 2008). Documentation of the scenario development process also improves transparency and communication of scenarios. This also encourages scenario developers to write down as explicitly as possible the techniques that have been applied and also the expert judgement that has been made. It is also important to gain insights into existing limitations of existing methods, avoid known pitfalls, and improve them where necessary. Relatively little information was encountered on this crucial component of the scenario development procedure during our literature review, as the assumptions and judgement made by experts were not written down explicitly in most cases. Hence, this is one area that deserves more attention than it has received in the literature. Progress can be made by developing and applying transparent and therefore reproducible methods, with clear and exhaustive documentation of their implementation in a particular application. Moreover, a transparent and open environment which allows extensive and efficient communication and interaction between experts, decision makers and stakeholders is necessary for the scenario development process.

2.6 Proposed probabilistic framework

In this section, a case is made for a probabilistic framework of developing scenarios for water resources planning and management that addresses some of the limitations identified in current studies. The framework relies on a Bayesian probabilistic model for the relevant driving forces (variables) shown in Figure 2.1, including climatic (C), socio-economic (SE), and water-related variables (W). Attaching probabilities to quantify these driving forces would lead to the probabilistic water scenarios, and then the weight that each scenario plays in developing water management plans is explicitly considered and quantified. The valuable information helps decision makers to rank the importance of alternative scenarios. Whereas probability and statistics is not the only framework available for dealing with future uncertainty, it provides a consistent and well-developed framework for accounting for uncertainty. In essence, adopting a Bayesian probabilistic view allows us to:

1. Use a variety of well-established and developed methods, such as the Principle Of Maximum Entropy (*POME*) and formal elicitation methods, for specifying continuous distributions of the driving forces, i.e. climate and socio-economic variables; besides, sensitivity analysis can be utilized when probability distributions are too difficult to be specified due to diverse views and assumptions from multiple experts;
2. Quantify resulting uncertainties in water-related variables (due to a combination of uncertainties in driving forces, models, and data) in a systematic and principled way by applying basic rules of probability, with flexible updating as new knowledge and data become available.

Uncertainties regarding the future evolution of all variables is represented by a joint probability density function (PDF), denoted by $p(C, SE, W)$, which can be translated as the probability of the occurrence of the future state comprising of the given climate scenarios, socio-economic scenarios and the resulted water scenarios. In other words, each set of specific values for C, SE, W is assigned a density value, quantifying our belief as to how likely it is that the particular given set of values will occur in the future. The use of a probability density function (as opposed to a probability mass function) implies that variables such as rainfall, temperature, population growth, and water supply are treated as continuous, as indeed they should. This is in contrast with previous Bayesian modelling studies, which typically rely on a discrete representation of continuous variables (Ames, Neilson et al. 2005, Groves 2006). Discretization of the values of a continuous variable into a finite set of intervals introduces unknown approximations and errors and should be avoided.

Applying basic rules of probability, and using the relations between SE, C, and W implied by the arrows in Figure 2.1, allows us to express the joint pdf in a more useful form:

$$p(SE, C, W) = p(SE)p(C|SE)p(W|SE, C) \tag{2.1}$$

where $p(SE)$, $p(C|SE)$, and $p(W|SE, C)$ quantify uncertainties in future values of, respectively, socio-economic, climate, and water-related variables. The vertical bar '|' is used to indicate probabilistic conditioning, e.g. $p(C|SE)$quantifies climate uncertainty given a particular value for socio-economic variables. The joint pdf, and therefore scenarios for SE, C, and W, can thus be computed by specifying each term in the expression above. We now outline several suggestions for how our proposed Bayesian probabilistic framework can be implemented using the general procedure of Figure 2.2.

Step 1 and 2 in Figure 2.2 can be implemented using existing methods as also applied in previous studies. However, progress can be made here by developing and applying transparent and reproducible methods that include clear and exhaustive documentation of their implementation in a particular application.

Step 3 – Quantify future development of driving forces (C, SE) according to the storyline

Using the notation adopted above, this step aims to quantify and specify distributions $p(SE)$ and $p(C|SE)$, from a set of qualitative narratives (storylines). As the knowledge of 'true' or objective scenario probabilities are impossible to obtain the probabilistic assessment is necessarily subjective relying on the available knowledge and judgment of experts, and a transparent and explicit procedure will be beneficial to expose biases behind the expert judgement We highlight two formal statistical methods that can be used for probabilistic assessment, namely prior elicitation and the Principle Of Maximum Entropy (*POME*). A large amount of literature is available on formal methods and protocols for eliciting probability distributions from experts (e.g.,Myung, Ramamoorti et al. 1996, O'Hagan, Buck et al. 2007). These methods allow identification of entire probability distributions for variables of interest (e.g.,Jaynes 1957, Gay and Estrada 2009). Elicitation methods are expected to be mostly useful for obtaining distributions for socio-economic variables, i.e. for specifying $p(SE)$, as models that predict future evolution of socio-economic systems are not as readily available as climate models.

In contrast, specifying distributions $p(C|SE)$ for climate variables for given socio-economic scenarios (typically GHG emission scenarios), can more easily be based on output from GCMs, as done in many previous studies. However, reliance on GCMs only produces a discrete set of scenarios, even if combining several GHG emission scenarios and several GCMs. The question is then how to convert this data into continuous distributions for relevant climate variables. It turns out that the *POME* is ideally suited for this purpose. The *POME* (Jaynes 1957) is a method originating from information theory for assigning the least-biased probability distribution given the available knowledge and data. In information theory, entropy is a measure of the uncertainty associated with a random variable represented by a probability distribution (Shannon 1948). Application of the *POME* to assign probability distributions to scenarios amounts to maximizing the uncertainty subject to constraints representing the current knowledge status. The method was applied in (Gay and Estrada 2009) for generating probabilistic climate change scenarios for the year 2100, given knowledge of the IPCC's likely ranges of climate variables together with different agents' judgement and subjective beliefs. The method has also been used to elicit probabilities from multiple experts, i.e. aggregating opinions from two or more experts for the prediction of the outcome of uncertain events (Myung, Ramamoorti et al. 1996). In that sense, it can be used in combination with the elicitation methods described above.

In case the two methods are not applicable and a consensus of probability assignment of the driving forces cannot be reached due to various gaps in knowledge and assumptions by the experts, sensitivity analysis provides a solution for utilizing all the possible probability distributions to generate water scenarios. The sensitivity of the resulting water scenarios on these diverse assumptions can be investigated as well. For example, different PDFs were assigned to climate variables, i.e. precipitation and temperature, to generate scenarios for additional water required to cope with climate change in the east of England. The sensitivity of the water scenarios to various climate change uncertainties were evaluated, as well as the robustness of water management strategies to these uncertainties (Dessai and Hulme 2007).

Step 4 - Quantify future development for water-related variables (W)

In the proposed probabilistic framework, this step involves specifying the conditional distribution $p(W|SE, C)$. A probabilistic hydrological model can be used for this purpose, as e.g. advocated in Schoups and Vrugt (Schoups and Vrugt 2010). Such a model combines physical knowledge in the form of water balance equations with a statistical description of residual model errors. Hence, the approach explicitly quantifies model uncertainties, which may be a significant part of the overall uncertainties. Hydrological and statistical parameters in these models may be estimated from historical data, as demonstrated in Schoups and Vrugt. Total or marginal uncertainty in water-related variables W may subsequently be computed using basic rules of probability: the joint distribution between all variables is first computed using Eq. 2.1, and variables SE and C are then integrated out (marginalized) to obtain the marginal or total distribution p(W), which quantifies total uncertainty over water-related variables, accounting for uncertainty in future values of driving forces (C, SE) as well as uncertainties related to converting driving forces into water-related variables. Such computations are most straightforwardly executed using Monte Carlo sampling (Nawaz and Adeloye 2006).

Step 5 – Refining and updating scenarios

Scenario refinement can be implemented through an iterative process, as discussed above. Updating scenario storylines as well as probabilities, however, is particularly elegant and natural in the probabilistic framework proposed here. Assume that an initial set of scenarios was generated according to the joint pdf $p(SE, C, W)$, by following steps 1-4. At a later time, say several years later, the scenarios are to be updated, for example, by taking into account new data D that has been obtained since the initial scenarios were produced. This new set of scenarios can be represented by a new joint pdf $p(SE, C, W|D)$, which can be obtained by application of the Bayes rule:

$$p(SE, C, W|D) \propto p(D|SE, C, W)p(SE, C, W) \tag{2.2}$$

where $p(SE, C, W)$is given by Eq. 2.1, and $p(D|SE, C, W)$ quantifies the extent to which the new observations fit with the original scenarios developed according to $p(SE, C, W)$.

One limitation of the proposed framework is that it relies on expert judgement for assigning probabilities, which is prone to bring bias and subjectivity. Generally speaking, it is very hard, if not impossible, to eliminate all subjectivity. Our proposed methodology addresses this issue in at least three ways. First, we rely as much as possible on formal methods, such as the principle of maximum entropy (*POME*) and the basic rules of probability, for quantifying and propagating uncertainties. We emphasize that *POME* assigns the least prejudiced probability in the sense that it utilizes all the information available but remains as non-committal as possible with information not available (Jaynes 1957, Myung, Ramamoorti et al. 1996). The use of Bayesian probabilities encourages people to explain their judgements explicitly such that these become open to peer review and criticism, thereby exposing hidden assumptions, biases, and expectations (Millett 2008). Second, if *POME* is not used, we advocate making explicit all the assumptions and expert judgments that feed into the mathematical models (e.g. specification of probabilities, elicitation of scenario storylines, etc.). Expert judgment remains an important component of environmental planning (Krueger, Page et al. 2012), and an explicit and transparent elicitation procedure is extremely important. Third, following good practice in the application of Bayesian methods, we propose the use of sensitivity analysis to evaluate to what extent the resulting scenarios and uncertainties are affected by various assumptions. In summary, we do not claim that the mathematical methods proposed here will magically solve all problems of subjectivity, however the methodology is geared towards minimizing and quantifying impacts of subjective decisions, and does not preclude use of advanced expert elicitation techniques that aim to reduce biases (e.g.,O'Hagan, Buck et al. 2007, Krueger, Page et al. 2012).

In short, the probabilistic framework can potentially be used to develop water scenarios to cope with the two limitations discussed in section 2.5. The approaches used in the framework are scientifically sound as they are well-established and well-utilized, which increases the credibility of the development process. The Bayesian-based framework provides the flexibility for updating the probabilistic water scenarios, by providing new perspectives and information to facilitate water resources management adapting to the changing futures.

2.7 Conclusions

Our review on scenario development in water resources planning and management illustrates the wide popularity of this approach to explore future water systems and assist strategic planning in an uncertain and complex world. Scenario development addresses uncertainties of three interdependent systems influencing the water system. We presented an iterative development procedure according to the reviewed scenario development studies. Techniques used for each step were summarized, aiming to provide information for the choice of proper techniques to develop scenarios. The main conclusions from this evaluation are that the qualitative and quantitative construction step, specifically, the 'continuous' and 'probabilistic' scenarios with explicit quantification of uncertainties, has not been adequately addressed in existing literature, as they are highly important for providing information for robust decision making. Finally, a probabilistic framework was proposed to address the above issues using existing techniques from information theory and statistics, pointing the way forward for scenario development practices in water resources planning and management.

Chapter 3 Probabilistic scenario development: *Climate change impact on future runoff in the Yellow River Basin (YRB), China*

3.1 Introduction

The Yellow River is the second longest river in China. It flows around 5500 km in north China, originating from the Tibetan plateau, going through the northern semiarid region, the loess plateau, the eastern plain, and finally discharging into the Bohai Sea (see Figure 3.1). Its drainage basin covers about 573,000 km^2, including 12.9 million hectares of farmland, 31% of which is irrigated with water from the Yellow River. The Yellow River Basin (YRB) holds 13% of the total cultivated area in China, while it only holds 2% of the country's water resources (CMWR 2002). It is of importance for China in food production and economic development, for example, it generated 16% of Chinese grain production and 12% of the country's GDP in 2000. In the YRB, annual evaporation varies from 850 to 1600 mm, whereas annual precipitation varies from 200 to 700 mm. Natural average annual runoff amounts to 53.3 km3 and the annual renewable water resources per capita are estimated at 588 m3, less than one third of the Chinese average level (Cenacchi, Xu et al. 2011). It is characterized by severe water scarcity: the ratio of surface water withdrawals to total water supply was up to 64% in 2008, which is one of the highest in the world. In the last two decades, the water-caused hazard has shifted from flooding to droughts in the Yellow River Basin due to increasing pressures from population growth, economic development and climate change (Xu, Fu et al. 2010). Climate change is posed to worsen water scarcity conditions in the YRB (Cenacchi, Xu et al. 2011).

Impacts of climate change on water availability are subject to large uncertainties, and scenario-based approaches have been widely used to account for these uncertainties. The four scenario families (*A1*, *B1*, *A2*, *B2*) for greenhouse gas emissions developed by the IPCC have been widely used to estimate climate change impacts on water resources (IPCC 2000). The four scenario families were written to describe the world about future economic, social, environmental and technological development. *A1* and *B1* are both global-oriented, and expect low population growth and rapid economic development. *A1* storylines diverges to three groups (*A1FI*, *A1B*,

This Chapter is based on "Probabilistic scenario development to analyse future runoff in the Yellow River Basin", C. Dong, G. Schoups, N. van de Giesen, Environmental Engineering and Management Journal, 2013.

A1T) due to the various technological change in the energy system, while *B1* is more environment-friendly with clean energy and improved resources efficiency. *A2* and *B2* scenario families both focus on the local or regional levels. *A2* narrates that high population growth and more fragmented and slower economic pattern than in other storylines. *B2* describes the world moderately with intermediate population growth and economic development, and environmental sustainability will become a significant issue. Most of the researches adopted the *A2* and *B2* storylines to describe the future development track of the YRB. For example, annual runoff in the entire YRB is projected to increase up to 2.2% for scenario *A2*, and 8.4% for scenario *B2* by the year 2020 compared with the baseline period (1961-1990), based on output from a single General Circulation Model (GCM) (Zhang, Fu et al. 2007). However, no single GCM can be considered 'best' or 'sufficient' to deal with the uncertainty, and it is important to utilize results from a range of models (Mote, Duffy et al. 2011), which can at least add information and understanding about the climate change. Moreover, realizing that not all future climate projections have equal likelihood of occurrence, the use of probabilities to explicitly quantify uncertainty is recommended. In this paper, a probabilistic framework of scenario development based on multiple emission scenarios and GCMs is proposed and used to assess the impact of climate change on water availability in the YRB.

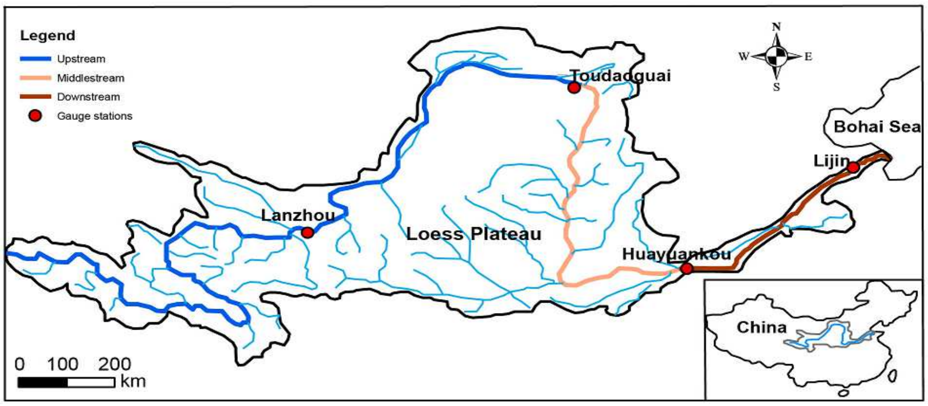


Figure 3.1 the Yellow River and Yellow River drainage basin.

3.2 Materials and methods

3.2.1 Materials

In order to develop climate change scenarios in the Yellow River Basin, the outputs of 11 GCMs (Table 3.1) using the IPCC emission scenarios *SRES-A1B*, *SRES-A2A*, and *SRES-B2A* were analysed for the period 2010-2039. The outputs were downscaled to a spatial resolution of 2.5 min using the Delta Method. This is a statistical downscaling method, which applies the surface of interpolated anomalies or deltas (changes in climate variables) to a high-resolution baseline (historical) climate grid from the WorldClim dataset (Hijmans, Cameron et al. 2005), accounting for bias due to the difference in baselines. Further description of the Delta downscaling method can be found in (Ramirez and Jarvis 2010). Another dataset is downscaled with 30 mins resolution using ClimGen from 7 GCMs, but only one scenario family *A1B* is available.

Table 3.1 General Circulation models (GCMs)

Model	Institute, Country	Reference
CCCMA-CGCM3.1(T47)	Canadian Centre for Climate Modelling and Analysis, Canada	(Scinocca, McFarlane et al. 2008)
CCCMA-CGCM3.1 (T63)	Canadian Centre for Climate Modelling and Analysis, Canada	(Scinocca, McFarlane et al. 2008)
CSIRO-MK3.0	Commonwealth Scientific and Industrial Research Organization, Australia	(Gordon, Rotstayn et al. 2002)
IPSL-CM4	Institute Pierre Simon Laplace, France	(Marti, Braconnot et al. 2005)
MPI-ECHAM5	Max Planck Institute, Germany	(Jugnclaus, Botzet et al. 2006)
NCAR-CCSM3.0	National Center for Atmospheric Research, USA	(Collins, Bitz et al. 2005)
UKMO-HADCM3	Hadley Centre for Climate Prediction and Research, UK	(Gordon, Cooper et al. 2000)
UKMO-HADGEM1	Hadley Centre for Climate Prediction and Research, UK	(Johns, Durman et al. 2006)
MRI-CGCM2.3.2	Japan Meteorological Agency, Japan	(Yukimoto, Noda et al. 2001)
MIROC3.2-HIRES	CCSR/NIES/FRCGC, Japan	(Hasumi and Emori 2004)
MIROC3.2-MEDRES	CCSR/NIES/FRCGC, Japan	(Hasumi and Emori 2004)

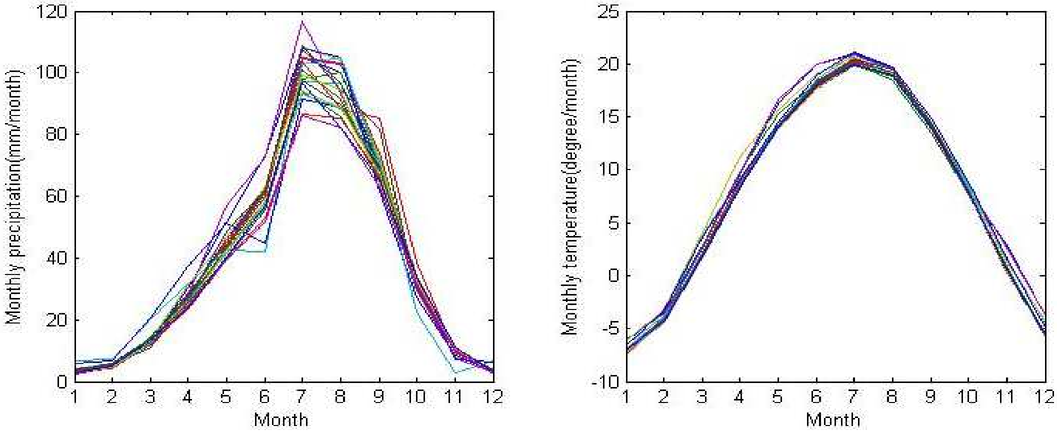


Figure 3.2 Monthly average precipitation and temperature in 2010-2039 from GCMs.

In order to simulate the rainfall-runoff process in the Yellow River Basin, monthly precipitation, pan evapotranspiration and natural runoff data above the Huayuankou gauging station were collected for the period of 1952-2000. The reason to simulate hydrological processes above Huayuankou gauging station is that the Yellow river below the Huayuankou station is suspended, and as a result, the natural discharge of the Huayuankou gauge station can be taken as the natural runoff from the whole Yellow River Basin. Figure 3.3 shows the mean and standard deviation of the monthly precipitation and temperature for the period 1961-1990.The standard deviation of monthly precipitation is big especially in summer and autumn, which is consistent with the change predicted by GCMs in Figure 3.2. The temperature has relatively small variation each month and is also consistent with its change in 2010-2039.

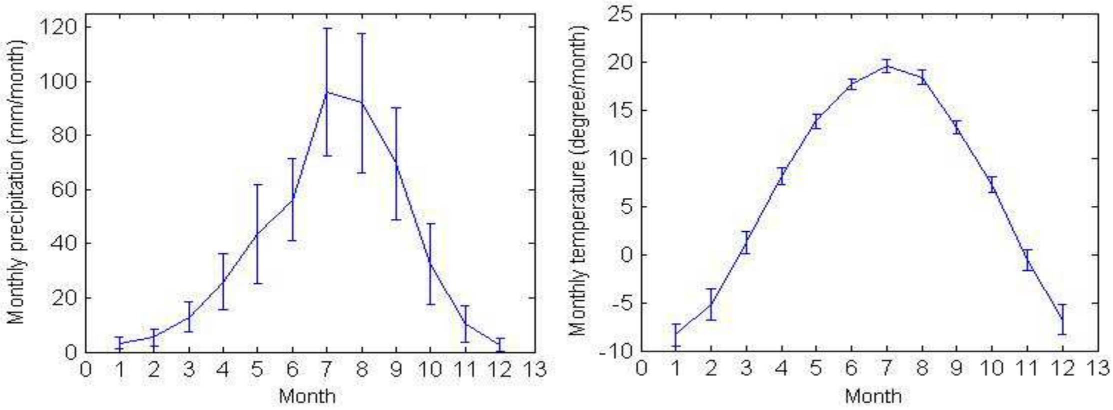


Figure 3.3 Mean and standard deviation of monthly precipitation and temperature in the YRB during 1961-1990.

3.2.2 Methods

Climate scenarios of future precipitation and temperature were developed based on the results of multiple GCMs. Probability distributions were assigned to future precipitation and temperature to explicitly represent a full set of future possibilities based on the Principle of Maximum Entropy (*POME*). Probabilistic climate scenarios were used as input to a conceptual hydrological model to simulate future river runoff to estimate climate change impacts on water availability. In this section, a description of the *POME*, and the conceptual hydrological model will be given.

3.2.2.1 Principle of Maximum Entropy (*POME*)

In 1984, Shannon introduced entropy into information theory as “a measure of how much ‘choice’ is involved in the selection of an event”. Shannon entropy was used to measure the uncertainty or chaos associated with a set of events when their occurrence is unknown but represented by a probability distribution. Shannon formulated the mathematically expression of entropy and applied it in the field of communications. If X is a discrete random variable with distribution given by

$$\Pr(X = x_k) = p_k \text{ for } k = (1,2,\dots,n) \tag{3.1}$$

Then the entropy of X is defined as

$$H(X) = -\sum_{k=1}^{n} p_k \, log_b p_k \tag{3.2}$$

If X is a continuous random variable with probability density $p(x)$, then the entropy of X is sometimes defined as

$$H(X) = -\int_{-\infty}^{\infty} p(x) log_b \, p(x) dx \tag{3.3}$$

Where unit of entropy is bit if the base b=2; nat for $b=e$, and dit (or digit) for b=10.

Jaynes contributed to the applications of entropy and proposed the Principle of Maximum Entropy (*POME*) in the 1950s. He stated that “the maximum entropy distribution is the least biased one which is maximally noncommittal with regard to missing information, and that it agrees with what is known, but expresses maximum uncertainty with respect to all other matters” (Jaynes 1957). The principle of maximum entropy is based on the premise that when estimating the probability distribution, the maximum entropy distribution, whose entropy is at least as great as that of all other members of a specified class of distribution, should be selected as it leaves the largest remaining uncertainty consistent with the constrains representing the available information. For example, given the mean and standard deviation, the normal distribution $N(\mu, \sigma)$ has the maximum entropy among all distributions with specified mean μ and standard deviation σ; similarly, given the mean value $1/\lambda$ and the variable is positive, the exponential distribution $Exp(\lambda)$ has the maximum entropy. In Bayesian probability, the principal of Maximum Entropy was a way to assign a prior probability distribution.

3.2.2.2 Hydrological model

A spatially lumped hydrologic model (Schoups, Vrugt et al. 2010) derived from the *FLEX* model framework (Fenicia, Savenije et al. 2007) is used to simulate the rainfall-runoff process. The simple hydrological model lumped partitions rainfall into runoff, evaporation and percolation into a surface and subsurface water storages. Snow accumulation and snowmelt is not taken into account. The model operates at the basin level, with no attempt to model the spatial distribution of hydrological process and storage in the basin. The hydrological model has been applied in the French Board Basin and a semiarid Guadalupe River Basin in the USA (Schoups and Vrugt 2010). The model consists of four reservoirs: an interception reservoir (*IR*) represents the interception process; an unsaturated soil reservoir (*UR*) denotes the soil storage capacity; a fast reacting reservoir (*FR*) accumulates the fast runoff and a slow reacting reservoir (*SR*) gathers the percolated runoff (Figure 3.4). The fluxes represent the routine through the reservoirs. Runoff generation is assumed to be dominated by saturated overland flow and simulated as a function of water storage. The mathematical expression of the model based on an unsaturated zone water balance equation is written as Eq.3.4 (Schoups, Vrugt et al. 2010):

$$S_{max}\frac{dS_r}{dt} = P_e - R_f - E_e - P_s \quad (3.4)$$

Where S_r is the relative storage ($=S/S_{max}$), S is total storage (L), S_{max} is maximum storage capacity (L),t is the time (T), P_e is the effective rainfall rate (L/T), E_I is the Interception rate (L/T), R_f is runoff generation rate (L/T), E_e is actual transpiration rate (L/T), and P_s is percolation rate (L/T). The interception rate is assumed to be negligible here, and effective rainfall P_e is approximately equal to observed rainfall. The other three fluxes in Eq. 3.4 are parameterized as functions of relative storage:

$$R_f = P_e f(S_r\,;\,\alpha_F), \quad E_e = E_p f(S_r\,;\,\alpha_E) \quad , P_s = P_{smax} f(S_r\,;\,\alpha_s)$$

$$Q_t = Q_f + Q_s, \qquad Q_f = \frac{dS_F}{dt} = K_f S_f, \qquad Q_s = \frac{dS_s}{dt} = K_s S_s \quad (3.5)$$

Where E_p is potential evaporation rate (L/T), P_{smax} is maximum percolation rate (L/T), and α_F, α_E and α_S are process-specific parameters, S_f, S_s are storage of fast and slow reacting reservoirs, K_f, K_s are time constant to characterize the discharge routing through the fast and slow reservoirs respectively. The flux function f is assumed to take the following form and is monotonically increasing from 0 to 1:

$$f(S_r\,;\,\alpha) = \frac{1-e^{-\alpha S_r}}{1-e^{-\alpha}} \quad (3.6)$$

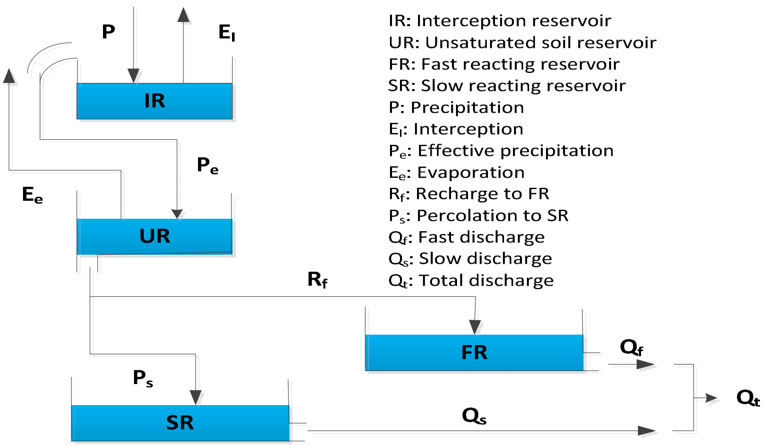


Figure 3.4 Hydrological model structure based on (Fenicia, Savenije et al. 2007, Schoups and Vrugt 2010).

A formal likelihood function was used for estimate the parameter uncertainty. The error of the hydrological model is modelled by a first-order, auto-correlated, heteroscedastic error model with a Skew Exponential Power (*SEP*) distribution which has a heavier tail than Gaussian distribution (Schoups and Vrugt 2010). The Generalized likelihood function improved estimation of parameter and total predictive uncertainty when applied to a daily rainfall-runoff hydrological model in French Broad basin and Guadalupe River Basin, USA. Additionally, it can be used for handling complex residual errors in hydrological models.

Table 3.2 Prior uncertainty range of hydrological and error model parameters

Parameter	Symbol	Minimum	Maximum	Units
Soil storage capacity	S_{max}	0	50000	mm
Maximum percolation rate	Q_{max}	0	3000	mm/month
Evaporation parameter	α_E	0	500	
Runoff parameter	α_F	0	300	
Time constant, fast reservoir	K_f	0	10	month
Time constant, slow reservoir	K_s	0	100	month
Heteroscedasticity slope	σ_1	0	1	
Autocorrelation coefficient	$\emptyset_1$	0	1	

3.3 Results

3.3.1 Probabilistic scenarios of climate variables

Precipitation and mean temperature in the YRB are the climate variables of interest here, as these will determine future hydrological conditions. Three assumptions are made in order to develop the probabilistic scenarios: (1) all the GCMs perform equally well, (2) the statistics (mean and standard deviation) of the multiple model experiments is generalized to approximately represent the ‘real statistics’, and (3) temperature will always increase in the future due to global warming. Probability distributions of the scenarios of the change of monthly precipitation and mean temperature (baseline period 1961-1990) in the period of 2010-2039 are assigned based on the Principle of Maximal Entropy. This results in a normal distribution for the change of precipitation, given the mean and standard deviation, and a lognormal distribution for the change of temperature, given the mean and standard deviation and assuming change is always positive (assumption 3 above). The probability density functions are thus:

$$\begin{gathered} \delta P_i \sim N(\mu_{\delta Pi}, \sigma_{\delta Pi}); \\ \delta T_i \sim lnN(\mu_{\delta Ti}, \sigma_{\delta Ti}) \\ i = 1,2, \ldots, 12 \end{gathered} \tag{3.7}$$

where $\delta P_i, \delta T_i$ represent changes in precipitation and temperature in the i-th month between future and baseline periods.

Probabilistic climate scenarios are then generated by Monte Carlo sampling. First, changes in precipitation and temperature for the period 2010-2039 are sampled from the generated probability density functions, which are converted into future monthly precipitation P_{fu}^i and temperature T_{fu}^i by adding the sampled changes to the baseline monthly values. Bootstrap sampling (Austin and Tu 2004) is used to sample the original baseline precipitation and temperature in each month to take into account the natural variability of the climate variables. Dong (2012) applied Bootstrap sampling to characterize the variability and uncertainty of hydro-climatic variables such as precipitation, temperature and runoff in the Yellow River Basin, given the historical data.

$$P_{fu}^{i} = P_{base}^{i*} + \delta P_i;$$
$$T_{fu}^{i} = T_{base}^{i*} + \delta T_i \text{ , } i = 1,2, \ldots ,12 \tag{3.8}$$

where P_{fu}^{i}, T_{fu}^{i} are the 'future' case of precipitation and temperature in the i-th month; $P_{base}^{i*}, T_{base}^{i*}$ are the baseline precipitation and temperature generated by bootstrap sampling from the original monthly values (historical record).

3.3.2 Posterior distribution of parameters and performance of the hydrological model

The generalized formal likelihood function is used to estimate the uncertainty of the model parameters by considering the residues. A Markov Chain Monte Carlo algorithm named *DREAM_ZS* (DiffeRential Evolution Adaptive Metropolis algorithm) (Vrugt, ter Braak et al. 2009) was used to generate posterior parameter distributions and predictive uncertainty (Schoups and Vrugt 2010). The monthly data between 1952-1990 are used to calibrate the model and generate the posterior distributions of the hydrological and error model parameters Figure 3.5).

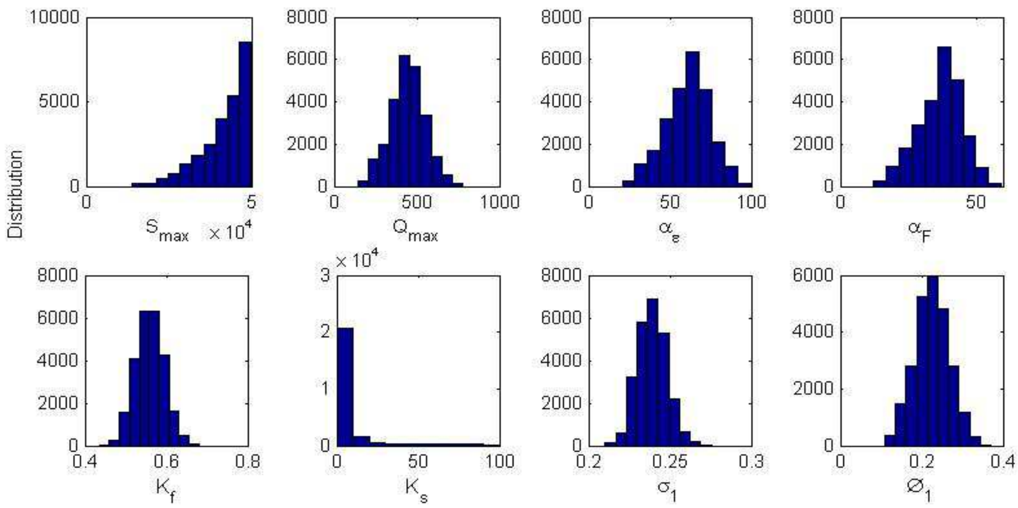


Figure 3.5 posterior distributions of hydrological and error model parameters.

The parameter set which has the maximum likelihood value given the observed data is optimal for the hydrological model. The period between 1991 and 2000 is used to verify the model. The graphs below (Figure 3.6) shows the observed natural runoff and the runoff simulated using the model.

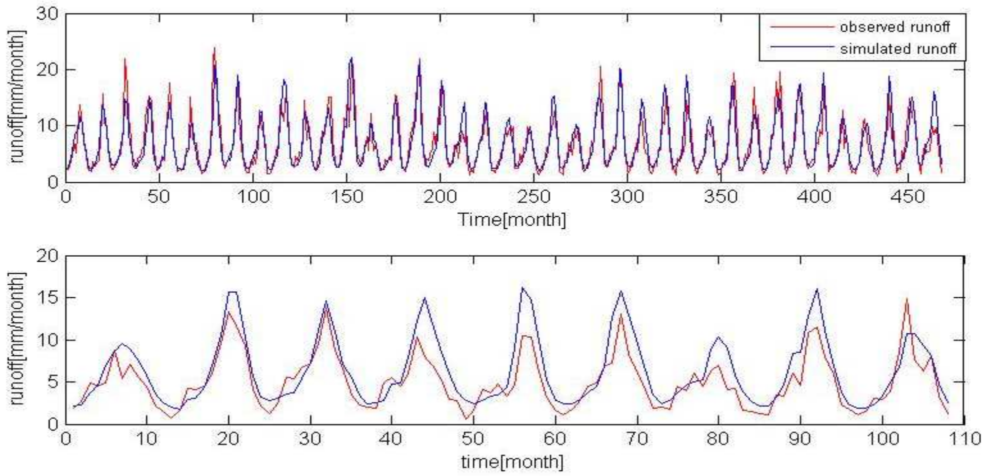


Figure 3.6 Model calibration and validation in the Yellow River Basin.

3.3.3 Runoff scenarios considering climate change

When analysing the potential impact of climate change on runoff in the period 2010-2039, probabilistic seasonal and monthly runoff are generated using the hydrological model based on the pre-defined scenarios of precipitation and temperature. The future pan evaporation is obtained based on an empirical relationship with temperature, which was derived from historical data (Figure 3.7). Future seasonal and monthly runoff is more informative and of practical interest compared with annual runoff. For example, water demand for irrigation in the YRB is large during the wheat growing seasons in winter and spring, when rainfall is scarce and irrigation is required; peak water demand for rice, which is also heavily irrigated, is in summer and autumn. Hence, information on changes in seasonal or monthly runoff, rather than annual, is needed for water management.

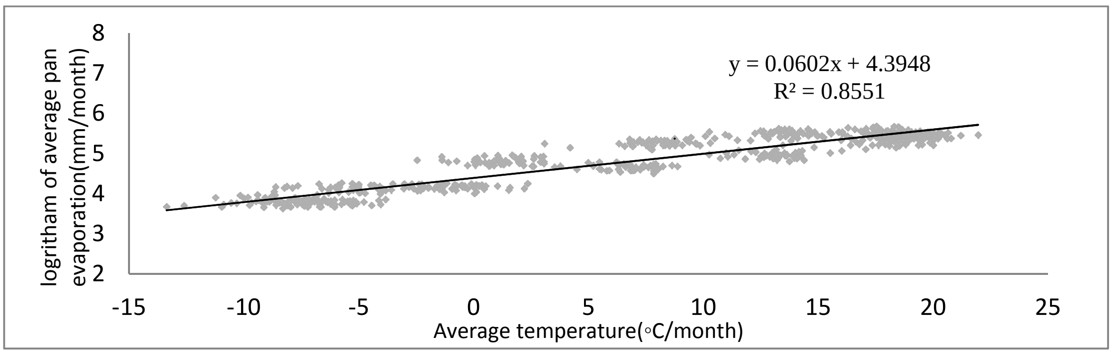


Figure 3.7 the relationship between monthly temperature and logarithm of pan evaporation of the YRB between 1951-2000.

Figure 3.8 show the average seasonal runoff (left) and the 90% uncertainty band (right) considering different uncertainty sources. Case *a* represents the runoff between1961-1990. Case *b, c, d, e* represent the predicted runoff between 2010-2039; case *b* considers only the input data uncertainty (i.e., probabilistic precipitation and temperature scenarios developed in section 3.1) with the optimal parameter set; case *c* accounts merely for the model parameters uncertainty; case *d* adds uncertainty in the model structure (residual uncertainty), and case *e* combines all sources of uncertainty (parameters, model structure, and climatic input). Table 3.3 shows the average value of runoff and the percentage of change in different conditions. In spring and autumn, runoff will decrease by around 25% and 12%. In summer and autumn, runoff will increase by a small percentage. The 90% uncertainty band of the runoff (figure 3.8 (right)) shows that the uncertainty due to the input data is slightly larger than that due to the hydrological model. It implies that to consider all different uncertainty sources is important as they are both significant.

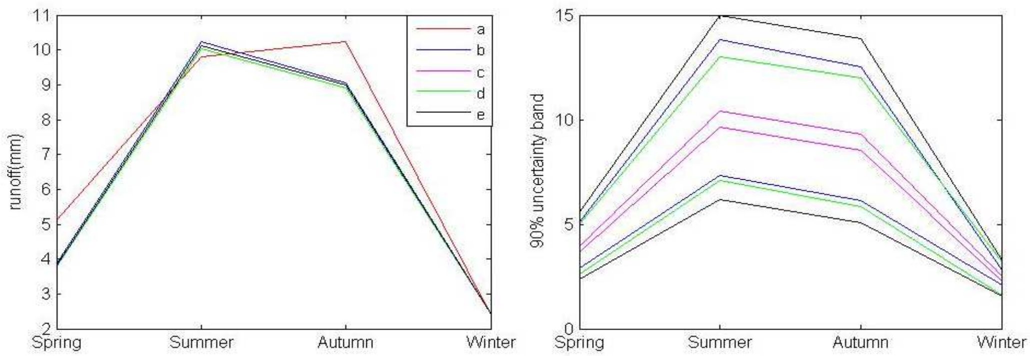


Figure 3.8 Average seasonal runoff (left) and the 90% uncertainty band (right) of the seasonal runoff considering different uncertainty sources: line *a* represents historical conditions (baseline), line *b* is the model prediction in 2020s without considering model uncertainty, line *c,d,e* are the runoff in 2020s considering the uncertainty from parameters, parameters plus model structure, and parameters, model structure and input data.

Table 3.3 Seasonal average runoff in historical and predictive conditions (mm)

	Spring	Summer	Autumn	Winter
Case *a*	5.11	9.80	10.23	2.38
Case *b*	3.86 (-24.37%)	10.25(4.59%)	9.06(-11.46%)	2.42(1.58%)
Case *c*	3.79(-25.81%)	10.04(2.42%)	8.91(-12.95%)	2.41(1.11%)
Case *d*	3.79(-25.87%)	10.04(2.47%)	8.91(-12.97%)	2.41(0.11%)
Case *e*	3.82(-25.22%)	10.12(3.27%)	9.00(-12.10%)	2.42(0.15%)

Compared with the average runoff, a probability distribution provides more information, such as the high and low runoff associated with their probabilities. Figure 3.9 shows results for the cumulative probability distributions (CDF) of seasonal runoff, respectively. Five cumulative probability distributions are shown for each season, and each line accounting for different sources of uncertainty on future runoff. In spring and autumn, the runoff is decreasing as the whole future CDF is shifted to the left, compared to historical conditions. For example, median values for the five cases (*a*-*e*) are 4.94, 3.81, 3.80, 3.79 and 3.75 mm respectively. During autumn, runoff also tends to decrease, and median values for autumn are 9.77, 8.88, 8.90, 8.86 and 8.70 mm. In summer and winter, the future CDFs are shifted slightly to the right, compared to historical conditions, indicating a slight increase in runoff: median values are 9.43, 10.02, 10.02, 9.99 and 9.85 mm for summer, and for winter 2.29, 2.40, 2.41, 2.41 and 2.40 mm. Figure 3.10 shows the CDF of monthly runoff, and the same coloured line represents the runoff accounting for the same uncertainty. In Mar., May, Oct. and Nov., the monthly runoff has a large decreasing.

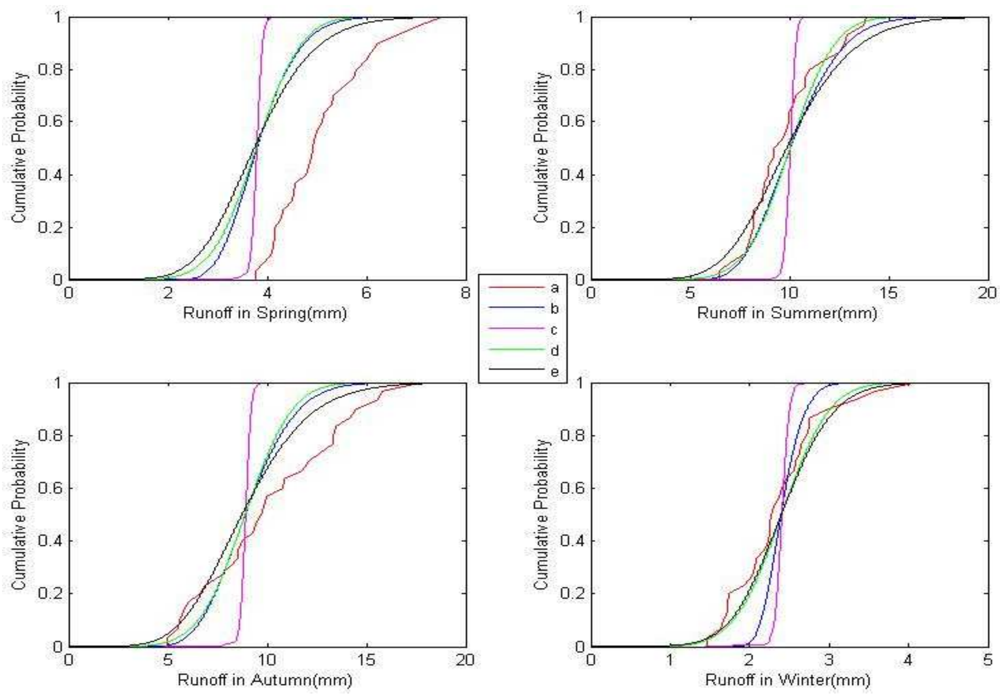


Figure 3.9 cumulative probability distributions of seasonal runoff

(The same colour line represents the same uncertainty source as in figure 3.8).

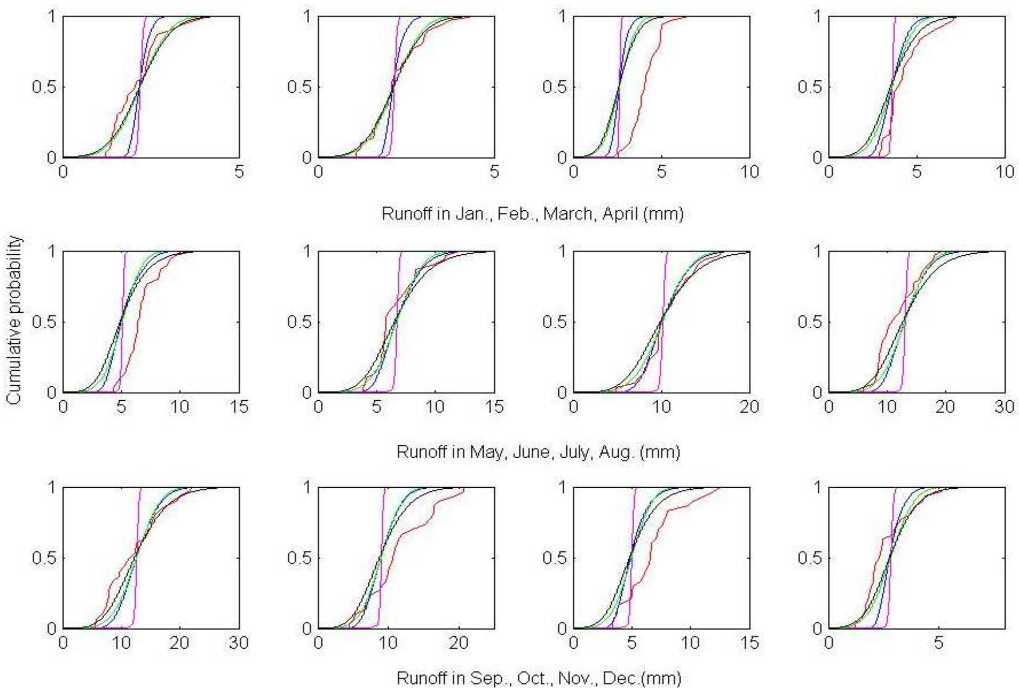


Figure 3.10 cumulative probability distributions of monthly runoff

(The same colour line represents the same uncertainty source as in figure 3.8).

3.4 Discussions and Conclusions

Scenarios of climate variables such as precipitation and temperature were developed based on multiple GCMs and IPCC emission scenarios, and lognormal distribution and normal distributions were attached to the two climatic variables respectively, using the Principle of Maximum Entropy. Seasonal and monthly runoff scenarios were generated to estimate future water availability under the impact of climate change. The results show that runoff for the period 2010-2039 is decreasing in spring and autumn, while in summer and autumn it slightly increases compared with baseline conditions. The methodology and results presented here complement and improve upon previous studies of the potential effects of future climate change on runoff in the Yellow River basin (e.g.,Zhang, Fu et al. 2007, Li, Hao et al. 2008, Xu, Fu et al. 2010). Zhang (Zhang, Fu et al. 2007) predicted that annual runoff in the Yellow River Basin is projected to increase up to 2.2% for IPCC scenario *A2*, and 8.4% for scenario *B2* (2010-2039) compared with the baseline period (1961-1990). The Yellow River Commission projected that the average runoff decrease by 16.99% under climate change (Xu, Fu et al. 2010). Our prediction is that annual runoff change is between the range of -18% to 7% under climate change impact, which almost covers all their results. From a methodological point of view, our work improves upon previous studies by (i) explicitly attaching probabilities to the various scenarios, as opposed to assuming all scenarios to be equally likely (for example, we develop probability distributions for precipitation and temperature using the Principle of Maximum Entropy), and (ii) by accounting for additional sources of uncertainty, such as hydrological modelling uncertainty, and errors in downscaling GCM output to local or regional scale. It has been investigated that the uncertainties from the climatic inputs and the hydrological model are both significant. The result is a set of fully probabilistic seasonal runoff scenarios that explicitly encompass a wide range of possible futures, which allows water managers to make robust decisions by testing strategies against the plausible range of future runoff in the face of climate change.

Chapter 4 Probabilistic scenario development: *Water demand projections in the Yellow River Delta (YRD), China*

4.1 Introduction

Scenario development is a useful tool to describe future states of the world under uncertainty, and probabilistic quantification of scenarios is desirable to provide explicit information to decision makers (Schneider 2001, Dong, Schoups et al. 2013). Noticing that it is difficult or even impossible to combine probabilities and scenarios objectively due to scientific uncertainty, subjective approaches are required to fulfil the task (Dessai and Hulme 2004). Subjective expert judgement/elicitation techniques have been widely used to elicit probabilities under uncertainty in studies such as environment studies, climate change and policy analysis (Morgan and Keith 1995, Titus and Narayanan 1996, Morgan, Pitelka et al. 2001, Webster, Forest et al. 2003, Zickfeld, Levermann et al. 2007, Low-Choy, James et al. 2012). The process of eliciting relevant knowledge and beliefs of experts to support probability elicitation or quantitative analysis is called expert elicitation (Low-Choy, James et al. 2012). Expert elicitation can be based on either a single expert or multiple experts, and it is assumed that a group of experts typically outperform a single one (Ferrell 1985). A challenge when using multiple experts is how to achieve consensus among their different opinions. In water resources planning and management, scenarios for variables such as population growth and irrigation water use, can be developed based on the judgement of experts, such as decision makers, hydrologists, stakeholders, and water managers. Additionally, future water supply and demand scenarios need to account for potential correlations between the variables of interest. Therefore, multivariate probability analysis is needed to model future water situations.

In this chapter, three issues are addressed in order: (1) How to quantify scenarios using expert judgment under uncertainty, (2) How to aggregate multiple experts' assessment into one single probability distribution, and (3) How to construct multivariate distributions to model dependence among variables.

This Chapter is based on "Scenario-based Expert Elicitation Approach for Future Water Demand Projection in the Yellow River Delta, China", C. Dong, G., Schoups, N. van de Giesen, 2014, under review.

4.1.1 Expert-elicitation for developing probabilistic scenarios

Expert-elicitation is suitable for specifying the probability distribution of an uncertain quantity, when available data is limited. A large amount of literature on expert elicitation has been published, both from statistical and psychological perspectives (e.g.,Garthwaite, Kadane et al. 2005, Choy, O'Leary et al. 2009, Krueger, Page et al. 2012, Low-Choy, James et al. 2012) . The use of expert elicitation in environment modelling under uncertainty due to data shortage has been reviewed by (Choy, O'Leary et al. 2009, Krueger, Page et al. 2012). Krueger et al. suggested that a formal and systematic use of expert opinions will benefit modelling under uncertainty and enhance the rigour of information that informs decision making. In psychological research, 'heuristics and biases' have been proposed by Tversky and Kahneman in 1970s (Tversky and Kahneman 1973) to describe human errors in assessing probabilities when facing uncertainty. Reviews about psychological research on expert elicited probabilities are provided by (O'Hagan, Buck et al. 2006, Kynn 2008). They both emphasised the necessity of taking into account the biases when managing expert elicitation. Despite the psychological constraints, Garthwaite reviewed statistical methods for expert elicited probability distributions and summarized several criteria to evaluate the quality of expert elicited probability distributions, pointing out that a successful elicitation should represent the opinion of the person being elicited, instead of how accurate the elicitation is in the objectivistic sense (Garthwaite, Kadane et al. 2005). Chhibber et al. outlined the problems of expert elicitation such as expert bias and dependence and addressed the difficulties to understand and treat them. They suggested that progress needs to be made to make expert opinions acceptable to the scientific community (Chhibber, Apostolakis et al. 1992).

4.1.2 Aggregating probability distributions from multiple experts

When eliciting with multiple experts’ opinions, the information needs to be aggregated in order to obtain a single probability distribution. The aggregation can be solved using either behavioural or mathematical methods. Behavioural methods aim to achieve some kind of consensus through interactions, discussions and negotiations among experts, for example, the Delphi method, the Nominal Group method, decision conferencing and Kaplan’s approach (Clemen and Winkler 1999). Mathematical methods range from simply taking the arithmetic or geometric means of probabilities assessed by experts to complex models such as axiomatic approaches (weighting scheme by using expert opinions) and Bayesian approaches (updating scheme by using expert opinions). Recently, the focus of mathematical methods has shifted to Bayesian approaches since a Bayesian paradigm was clearly formed for aggregating expert’s opinions by (Winkler 1968, Morris 1977). Bayesian models were first developed and applied for combining probability distributions when they are normally distributed (Winkler 1981). Mendal and Sheridan developed Bayesian models when probability distributions are not necessary normally distributed (Mendel and Sheridan 1989). Jouini and Cleman employed a copula function to estimate the likelihood function in the Bayesian model (Jouini and Clemen 1996). Clemen and Winkler (1999) tried to answer the question "what is the best way to combine the judgement?" by comparing the two categories of methods. They have reviewed a variety of mathematical methods through several studies, and found out that, in general, simpler aggregation mathematical methods such as simple models by putting equal weights to probabilities assessed by experts perform as well as more complex methods. Besides, by comparing the simple and weighted average method with behavioural methods, empirical studies show that the behavioural methods work slightly better or approximately at the same level as the mathematical methods.

4.1.3 Multivariate analysis given specified marginal distributions

In uncertainty and decision making analysis, it is often required to consider multivariate analysis through constructing multivariate joint probability distributions from specified marginal distributions (Clemen and Reilly 1999, Fang, Fang et al. 2002). Statistical studies have investigated the multivariate dependence structures given the specified marginal distributions. Meta-Gaussian distribution were constructed to model bivariate densities in hydrology (Kelly and Krzysztofowicz 1997). Fang extended the bivariate densities to a new class of distributions called meta-elliptical distributions (Fang, Fang et al. 2002). These methods are both based on the *copula* technique. Copula is derived from the Latin word "copulare", meaning to connect or join (Schmidt 2006). The concept has been recognized in the statistical field since (Sklar 1959). A copula is a tool for modelling the dependent relationship of multiple random variables. A number of copula functions has been defined, important copulas such as Gaussian copula, Farlie-Gumbel-Morgenstern class of copula (Johnson and Kott 1975), and Archimedean copulas family including parametric Clayton copulas (Clayton 1978), Frank copula (Frank 1979) and Gumbel copula. Genest and Rivest (Genest and Rivest 1993) studied the statistical properties of the Archimedean copulas. Bhat and Eluru (Bhat and Eluru 2009) reviewed the properties of these copulas and applied them to model residential self-selection effects in travel behaviour in the US. Recently, copulas have been applied in finance, econometrics, actuarial studies, hydrological modelling, drought analysis, travel behaviour modelling and healthcare fields (Kelly and

Krzysztofowicz 1997, Cherubini, Luciano et al. 2004, Frees and Wang 2005, Zimmer and Trivedi 2006, Genest and Favre 2007, Bhat and Eluru 2009, Shiau and Modarres 2009).

This chapter provides a scenario-based expert elicitation framework to probabilistically explore future scenarios under uncertainty, and copula-based methods to do multivariate analysis when dependence among variables is taken into account. At the end, a case study on water demand projection in the Yellow River Delta, China, is presented. Expert elicitation is guided by the well-structured SHELF procedure, and the experts' judgement will be aggregated using a mathematical approach. In modelling water demand, it is important to take into account the interrelationship among the variables, for instance, variables such as population growth and the per capital water demand. The projection of water demand in the next 30 years will inform and benefit the water resources planning and management in the Yellow River Delta.

4.2 Expert Elicitation of Priors: SHELF METHOD

In this research, SHELF (the Sheffield Elicitation Framework) is applied for probability elicitation through the interaction between experts and facilitator (who can be the decision maker or some relevant person). It provides the platform to capture expert's knowledge and feedbacks dynamically and graphically. SHELF is a freely available package, including some basic software in the R language. Currently, a new version SHELF2.0 is available (Oakley and O'Hagan 2010). SHELF has been used in a variety of fields to elicit experts' judgement in the Bayesian inferential framework (Higgins, Dryden et al. 2012, Higgins, Dryden et al. 2012, Ren and Oakley 2012, Kinnersley and Day 2013, Scholten, Scheidegger et al. 2013).

Before entering the elicitation stage, several things are essential and should be set up. (i) the experts who have special knowledge about the uncertain quantity of interest, and a facilitator who is familiar with the elicitation process should be identified. (ii) the facilitator should explain the purpose and importance of the elicitation to the participated experts. (iii) the participants will receive some 'training' to familiarise the process, and an evaluation about their strengths and weaknesses. The evaluation will be useful to beware of the deficiency and bias of the group's knowledge. (iv) all available relevant evidence about all the quantities of interest should be reviewed by the participants, in order to avoid their biased or impaired judgement based on partial evidence. (v) the participants can help structure and choose quantities which are easier to elicit. For example, to decompose quantities into independent quantities can avoid the estimation of joint probability, as the SHELF framework is not set up for joint probability assessment. The last task of the preparation is to define the chosen quantities.

To elicit a distribution of the predefined variable θ, four general steps can be done (Figure 4.1):

1. The expert makes a small number of probabilistic judgements about θ;
2. The facilitator fits a suitable parametric probability distribution to the expert's judgements;
3. The facilitator reports the fitted distribution to the expert(s), and ask if the distribution is acceptable based on their beliefs;
4. If the distribution is acceptable to the expert(s), then the elicitation can be completed. Otherwise, the facilitator fits an alternative distribution according to additional probabilistic judgement form the experts.

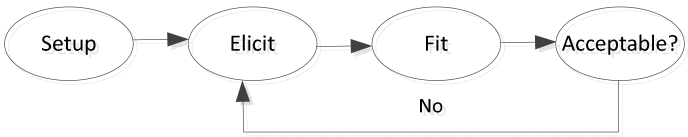


Figure 4.1 The elicitation process of SHELF method.

SHELF accommodates several different protocols for eliciting a distribution of the predefined variable in the first step. The probability method elicits the probability distribution by asking experts for some specified probabilities. The Quartile method uses the expert estimation of the median and upper/lower quartiles of the distribution. The Roulette method asks experts to indicate their probabilities for ten bins of values; and the Tertile method asks the experts for their median and upper/lower tertiles (Oakley and O'Hagan 2010).The facilitator is free to choose which protocol to use. In this study, the quartile method is used and the way to assess the probability of predefined variable θ is as follows:

1.1. Elicit plausible ranges *(L, U)* of the quantity which are agreed by all experts.

1.2. Specify the median value *M*, where $P\ (\theta < M)$ and $P\ (\theta > M)$ are equal, by the experts separately.

1.3. Specify lower and upper quartile *(Q1,Q2)*, when $P(L < \theta < Q1) = P(Q1 < \theta < M) = P(M < \theta < Q2) = P(Q2 < \theta < U) = 0.25$. The facilitator can ask them to adjust their values if necessary.

When a group of experts participate in the elicitation process, mathematical methods or behavioural methods are required to aggregate experts' opinions into a single probability distribution. In SHELF, a behavioural method is used to combine experts' assessment to fit a single probability distribution. Discussions and interactions among experts are encouraged to specify group consensus judgement for the probability distribution, for instance, in the quartile method, an agreement on the values for the median and quartiles is required. To fit a final distribution, revision of the group judgement is allowed according to their feedback.

4.3 Aggregating experts' probability distributions

4.3.1 Axiomatic approaches

Axiomatic approaches aggregate probabilities based on axiom-based aggregation formulas. A simple approach is called the *linear opinion pool*, to aggregate probability distribution by linearly weighting the opinions from experts.

$$p(\theta) = \sum_{i \to n} \omega_i \, p_i(\theta) \tag{4.1}$$

Where n is the number of experts, $p_i(\theta)$ is the probability assessment of the variable θ from the ith expert; ω_i are the weights, summing to 1; $p(\theta)$ is the combined probability distribution of θ.

For mixing the probability distributions into a single one, the (raw) moments of the mixture are the weighted average of the same moments of the component distributions (Frühwirth-Schnatter 2006). For example, the first and second moment of the mixed probability distribution when the component is normal distributed is:

$$\mu(\theta) = \sum_{i \to n} \omega_i \, \mu_i(\theta)$$

$$\sigma(\theta)^2 = \sum_{i \to n} \omega_i \, (\sigma_i^2 + (\mu_i - \mu)^2) \tag{4.2}$$

Where μ_i is the mean of probability distribution given by the ith expert, σ_i is the standard deviation of each component distribution.

Allocating weights to different experts is a subjective process. Various methods were reviewed by (Genest and McConway 1990) . Normally, the weight can be interpreted as "the better an expert, the heavier the weight ought to be attached to his/her opinion". The calibration approach has been widely employed to assess the quality of an expert's judgement. The approach requires experts to give plenty of probability assessments on many variables, and the ability of the experts' probability assessment can be measured by their performance (Morris 1977). In the Classic Model, three different weighting schemes, namely equal weighting, global weighting, and item weighting, were developed and distinguished by the ways how weights are assigned to the experts' assessment (Cooke 2013).

Although the linear pooling approach was shown to perform as good as more complex methods in aggregating opinions from experts, there is one disadvantage of the approach in that the dependence among experts' judgement is not taken into account (Clemen and Winkler 1999). In the next section, methods based on a Bayesian approach to consider the interrelationship will be briefly reviewed.

4.3.2 Bayesian approaches

Experts often have similar training, background and experience, and they are prone to provide redundant and dependent information. The impact of dependence on the precision and value of information has been investigated, and the results indicate that positive dependence among information sources can have a serious negative effect on the precision and value of the information (Clemen and Winkler 1985). Dependence among experts' judgement is an important and unavoidable source of difficulty. Morris (Morris 1983) pointed out that 'one of the future challenges in the field of expert modelling is the construction of general models of expert dependence. In expert-aggregating probability distributions problems, empirical studies have found that correlations among expert judgement in forecasting can be quite high, typically above 0.8 (Jouini and Clemen 1996).

To cope with dependence among experts, a Bayesian approach has been used for combining probabilities from experts' elicitation. Expert judgement can be used to elicit prior subjective probability distributions based on their available knowledge and beliefs. The prior probability judgement can be aggregated to elicit the posterior probability distribution. The Bayesian approach then provides the theoretical basis for expert-elicited probability estimation (Morris 1977, Varis and Kuikka 1997, Choy, O'Leary et al. 2009).

$$f(\theta|g_1, g_2, \cdots, g_n) = \frac{f(g_1, g_2, \cdots, g_n|\theta)\cdot g(\theta)}{\int f(g_1, g_2, \cdots, g_n|\theta) g(\theta) d\theta} \propto f(g_1, g_2, \cdots, g_n|\theta) g(\theta) \quad (4.3)$$

Where θ is the quantity whose probability distribution is estimated, g_i denotes the probability distribution of θ estimated by expert i.

$g(\theta)$: the prior probability distribution about θ. Usually, the prior probability is assessed by experts or decision makers. However, hindsight bias occurs when the experts already have partial historical information about θ, and have to give priors by pretending they don't know about it (Fischhoff 2003). To avoid the risk, non-informative priors, 'Sceptical' or 'Enthusiastic' priors (Abrams, Myles et al. 2004) given by decision-makers could be used.

$f(g_1, g_2, \cdots, g_n|\theta)$: the likelihood function. It reflects the expert's probability assessment conditional on the 'true' values of θ. When a group of dependent experts participant the probability assessment, the likelihood function is the joint probability assessment over the expert set.

$f(\theta|g_1, g_2, \cdots, g_n)$: the posterior probability of θ given the expert's judgement.

The format of Bayesian models to aggregate experts' judgement is determined by the marginal distributions and the construction of the likelihood function $f(g_1, g_2, \cdots, g_n|\theta)$. However, it is difficult to estimate an appropriate likelihood function, as a probabilistic model has to be constructed to capture the interrelationships among θ and $g_1, g_2, \cdots, g_n$, as well as the dependence among the bias and errors from different experts' judgement $g_1, g_2, \cdots, g_n$.

For aggregating probability estimation of a discrete event from a group of experts, four different likelihood functions were constructed in the Bayesian paradigm. The four likelihood functions were constructed based on the independence model, Genest and Scherivish linear regression model (Genest and Schervish 1985), Bernoulli sampling (Morris 1983), and multivariate normal model (French 1981), respectively. For aggregating probability distributions assessed from a group of experts, Error density function such as a Normal Model (Winkler 1981) and Copula functions (Jouini and Clemen 1996) were used to capture the dependence among experts judgement and construct the likelihood function in Bayesian models. The normal model (Winkler 1981) specifies the dependence among experts based on the density function of expert' judgement errors. However, the model was only suitable for the normally distributed marginal, and the aggregated distribution is also normal distributed. The Copula-based model (Jouini and Clemen 1996) captures the dependence among a set of experts with one single parameter, the concordance probability, which is cognitive and also not flexible if different levels of dependence needs to be captured. Additionally, the two methods are sensitive to the dependence level among experts' judgement.

4.4 Copula-based models for multivariate analysis

4.4.1 Basis of Copula

A copula is used for modelling dependence of several random variables, and is derived from the Latin word "copulare", meaning to connect or join (Schmidt 2006). A copula function serves as a dependence function, and represents a distribution on the unit square with uniform marginal distribution. It can be used to link the joint multivariate function and their marginal distribution functions, encoding dependence among different information sources and marginal distributions. One advantage of copulas is that the dependence assessment is separate from the marginal distributions, and the marginal distributions can be formulated independently.

Sklar's Theorem (Sklar 1959): Given a joint cumulative distribution function $F(x_1, \cdots, x_n)$ for random variables $X_1, \cdots, X_n$ with marginal cumulative distribution functions $G_1(x_1), \cdots, G_n(x_n)$. Then the joint cumulative distribution can be written in the form of copula:

$$F(x_1, \cdots, x_n) = C[G_1(x_1), \cdots, G_n(x_n)] \tag{4.4}$$

Where $C[u_1, \cdots, u_n]$ is a joint distribution function with uniform information marginal, and it is called a Copula. If G_i is continuous, then C is unique, and if G_i is discrete, then C is unique on $R(G_1) \times \cdots \times R(G_n)$, where $R(G_i)$ is the range of G_i.

Given that G_i is continuous and differentiable, the joint density $f(x_1, \cdots, x_n)$ can be written as the product of the marginal densities and the copula density. Then,

$$f(x_1, \cdots, x_n) = g_1(x_1) \times \cdots \times g_n(x_n) c[G_1(x_1), \cdots, G_n(x_n)],$$
$$c[G_1(x_1), \cdots, G_n(x_n)] = \partial^n C / (\partial G_1 \cdots, \partial G_n) \tag{4.5}$$

Where $g_i(x_i)$ is the density corresponding to $G_i(x_i)$, c is the copula density. c is independent from the marginal probability distributions. If these variables are independent, then $c = 1$, and $f(x_1, \cdots, x_n) = g_1(x_1) \times \cdots \times g_n(x_n)$.

4.4.2 Copula-based models

Three steps are required to apply copula-based probability models. First is to identify the marginal probability distributions, second is to model the dependence among the information sources or variables, and third is to identify an appropriate copula function. In this section, the measures to assess correlation and two important copula functions will be mentioned.

4.4.2.1 Correlation assessment

To measure the dependence, the product moment correlation ρ, rank-order correlations such as the Spearman's ρ_s and Kendall's τ are sufficient in constructing several copula families. The explanation of these correlations and their properties can be found in (Kurowicka and Cooke 2006). A brief description of these dependence measures is given below.

(1) Product moment correlation ρ

The Product moment correlation ρ is also called linear or Pearson correlation. The product moment correlation of two random variables X, Y is defined as:

$$\rho(X,Y) = \frac{E(XY)-E(X)E(Y)}{\sigma_X \sigma_Y} \tag{4.6}$$

Where $E(X)$, $E(Y)$ and σ_X, σ_Y are the expectations and standard deviation of X, Y,respectively. $|\rho(X,Y)| \leq 1$. If $\rho(X,Y) = 0$, the two variables are independent. If $\rho(X,Y) > 0$ (< 0), then the two variables are positively (negatively) correlated. Larger values imply stronger correlations.

Statistical estimation and expert judgement can be applied to assess the correlation. When estimation is statistical, the correlation depends on the linear regression between the data of two variables; when estimation is judgemental, the experts are supposed to be familiar with the statistical concepts related to correlation, and are capable to make a reasonable assessment of the bivariate relationships. Research has been done about directly eliciting correlation between variables, for example, Gokhale and Press (Gokhale and Press 1982) showed that individuals with statistical knowledge are able to assess the correlation between two data sets by reading their scatterplot. Clemen (Clemen, Fischer et al. 2000) compared six methods to elicit a correlation between weight and height in a population of male MBA students, and found that direct estimation of the correlation by specifying a value between -1 and 1 performed better than the other five methods, such as asking individuals to estimate the Kendall's τ between the two variables. Garthwaite suggested that graphic methods perform better to describe the linear regression between two variables. For two variables X and Y, to elicit points from the regression function $m(x) = E(Y|X = x)$ allows the estimation of the correlation if the experts believes their relationship is linear (Garthwaite, Kadane et al. 2005).

(2) Spearman correlation

The rank or Spearman correlation $\rho_S(X,Y)$ of two random variables X, Y with joint probability distribution $F_{X,Y}$ and the marginal probability distribution F_X and F_Y, respectively, is given by:

$$\rho_s(X,Y) = \rho(F_X, F_Y) \tag{4.7}$$

Where $\rho(F_X, F_Y)$ denotes the product moment Pearson's correlation.

$$\rho(F_X, F_Y) = \frac{cov(F_X, F_Y)}{\sqrt{var(F_X)var(F_Y)}} \tag{4.8}$$

Unlike the product moment correlation, the Spearman correlation always exists and it is independent of the marginal distributions. Hence, it can be a suitable measure for techniques that are required to be independent of marginal probability distributions, such as the copula between two random variables.

(3) Probability of Concordance to estimate Kendall's τ.

Concordance measures the extent to which a set of random variables tends to be identical from the ordering of another set of variables. Conversely, the dependence relation is called discordant. Let $(X_{1i}, X_{2i} \cdots, X_{ni})$ and $(X_{1j}, X_{2j} \cdots, X_{nj})$ be two independent and identically distributed *n*-tuples of random variables. They have the same distribution as $(X_1, X_2 \cdots, X_n)$. The random variables $(X_1, X_2 \cdots, X_n)$ are concordant if

$$X_{1i} < X_{1j}, X_{2i} < X_{2j} \cdots, X_{ni} < X_{nj} \text{ or}$$

$$X_{1i} > X_{1j}, X_{2i} > X_{2j} \cdots, X_{ni} > X_{nj},$$

The probability of concordance Pc of $(X_1, X_2 \cdots, X_n)$ is

$$Pc = P(X_{1i} < X_{1j}, X_{2i} < X_{2j} \cdots, X_{ni} < X_{nj}) \text{ or}$$

$$P(X_{1i} < X_{1j}, X_{2i} < X_{2j} \cdots, X_{ni} < X_{nj}$$

The Kendall's τ can be related to Pc;

$$\tau = 2Pc - 1 \tag{4.9}$$

If two random vectors (X,Y) are from the bivariate normal distribution, the relationship among Spearman's $\rho_s(X,Y)$, Kendall's $\tau(X,Y)$, or the Persons correlation $\rho(X,Y)$ can be written as (Kruskal 1958):

$$\rho(X,Y) = sin(\frac{\pi\tau(X,Y)}{2}) , \ \rho(X,Y) = 2sin(\frac{\pi\rho_s(X,Y)}{6}) \tag{4.10}$$

4.4.2.2 Copula functions

A series of copula families and their characteristics have been explained in (Kurowicka and Cooke 2006, Bhat and Eluru 2009). Among them, two copulas, i.e. the *Archimedean copula* and the *Gaussian copula*, which are very popular, are briefly explained.

Gaussian Copula is derived from a multivariate normal distribution. It is comprehensive in obtaining the Frechet lower and upper bounds and capturing the full range of dependence (both positive and negative) (Bhat and Eluru 2009). The Gaussian copula with a correlation matrix *R* is written as:

$$C_{\mathrm{R}}^{Gauss}(u) = \Phi_{\Sigma}(\Phi^{-1}(u_1), \cdots, \Phi^{-1}(u_n)) \tag{4.11}$$

$$R = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

Where $\Phi_{\Sigma}(\Phi^{-1}(u_1), \cdots, \Phi^{-1}(u_n))$ is the multivariate normal distribution with zero mean and correlation matrix R, ρ is the product Person's moment correlation, and Φ is the CDF of a standard normal distribution.

The Gaussian copula density $c_{\Sigma}^{Gauss}(u)$ is written as:

$$c_{\mathrm{R}}^{Gauss}(u) = \exp\left(-\frac{1}{2}\begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_n) \end{pmatrix}^T \cdot (\mathrm{R}^{-1} - \boldsymbol{I}) \cdot \begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_n) \end{pmatrix}\right) \Big/ |\mathrm{R}|^{\frac{1}{2}} \tag{4.12}$$

Where *T* represents the vector transpose, and ***I*** is the identity matrix.

To generate uniform random variates from the Gaussian Copula (Schmidt 2006), one can use the following algorithm:

1. For an arbitrary covariance matrix $\tilde{\Sigma}$ obtain the correlation matrix Σ.
2. Perform a Cholesky-decomposition $\Sigma = A^T A$.
3. Generate idd standard normal pseudo random variates $\widetilde{\mathrm{X}_1}, \cdots, \widetilde{\mathrm{X}_d}$.
4. Compute $(X_1, \cdots, X_d)^T = X = A\tilde{X}$ from $\tilde{X} = (\widetilde{\mathrm{X}_1}, \cdots, \widetilde{\mathrm{X}_d})^T$.
5. Return $U_i = \Phi(\mathrm{X}_i), i = 1, \cdots, d$ where Φ is the standard normal cumulative distribution function.

The correlation matrix Σ has to be a valid matrix in order to perform the Cholesky-decomposition. A valid matrix has the important properties such as all entries should between [-1,1], with 1 along the main diagonal, symmetric and positive semi-definite (PSD). To be a positive semi-definite matrix, the eigenvalues of the matrix should be positive, and the determinant of the matrix should be non-negative. However, the matrix elicited is not always positive definite; Nicholas J. Higham's algorithm can be applied to find the closest valid correlation matrix (Higham 2002).

Figure 4.2 shows scatter samples from the Gaussian copula-based bivariate distribution with a correlation parameter $\rho = 0.9239$ and two normal marginal distributions. The samples are symmetric around the central points, called radially symmetric, and are away from the tails. It shows that the Gaussian copula is radially symmetric, with strong dependence in the middle and weak dependence in the tails of the marginal distributions.

The Archimedean copula can be defined *iff* (if and only if) there exists a convex and strictly decreasing function $\varphi: (0,1] \to [0, +\infty)$, with $\varphi(1) = 0$. $\varphi'(x) < 0$, and $\varphi''(x) > 0$ for all $0 < x < 1$. $\varphi(0) = \infty$, then the inverse function φ^{-1} exists. Thus, the bivariate Archimedean copula is:

$$C_2(u_1, u_2) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2)) \tag{4.13}$$

To extend to higher dimensions:

$$C_n(u_1, \cdots, u_n) = \varphi^{-1}(\varphi(u_1) + \cdots + \varphi(u_n)) \tag{4.14}$$

Where $u_1, \cdots, u_n$ are marginal cumulative probability distributions of the random variables. φ is the generator function. For example, $\varphi(x) = \frac{1}{\theta}(t^{-\theta} - 1)$ generates the Clayton copula; $\varphi(x) = -ln\frac{e^{-\theta x}-1}{e^{-\theta}-1}$ generates the Frank copula; where θ is the dependence parameter.

Frank copulas, for example, are the only class of one-parameter Archimedean copulas allowing negative dependence and obtaining the Frechet lower and upper bounds. The Frank-copula form of a bivariate distribution is:

$$C_{2|\theta} = -\frac{1}{\theta} ln\left[1 + \frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}\right], \ -\infty < \theta < \infty, \theta \neq 0 \tag{4.15}$$

With $$\varphi(x) = -ln\frac{e^{-\theta x}-1}{e^{-\theta}-1}$$

Where θ is the only parameter to decide the dependence level between variable X_1, X_2, and Jouini (Jouini and Clemen 1996) listed the corresponding values of θ and Kendall's τ; u_1, u_2 are marginal cumulative probability distributions of variable X_1, X_2 to construct a bivariate distribution, $(u_1, u_2) \in [0,1]^2$. To extend the copula function to the multi-dimensional form,

$$C_{n|\theta} = -\frac{1}{\theta} ln\left[1 + \frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)\cdots(e^{-\theta u_n}-1)}{(e^{-\theta}-1)^{n-1}}\right], \ n \geq 2 \tag{4.16}$$

Figure 4.2 shows samples from a Frank copula with a correlation parameter $\theta = 14.14$ and the same marginal distributions. As with the Gaussian copula, the Frank copula has a radially symmetric dependence.

In Archimedean copulas, the single dependence parameter, Kendall's τ, is shared by all marginals of interest. It is difficult to estimate it in practice. More flexible structures are required to be constructed for high dimensions if Archimedean copulas are used to analyse multivariate joint distributions (Zimmer and Trivedi 2006).

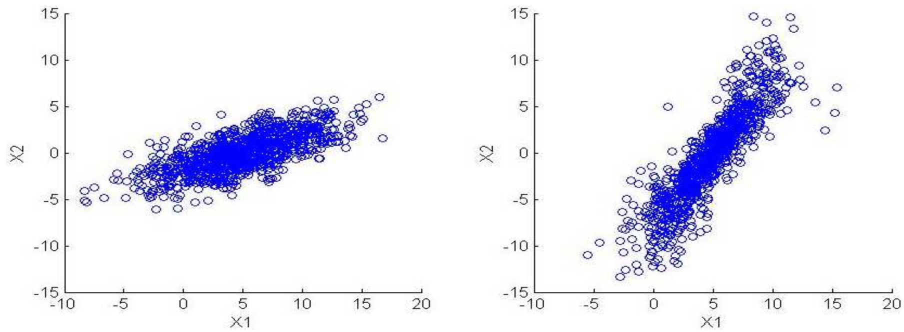


Figure 4.2 Bivariate copula plots. Left: Gaussian copula $\tau = 0.75, \rho = 0.9239$, Right: Frank copula $\tau = 0.75, \theta = 14.14$, with marginal distributions $X_1 \sim N(5,3)$ and $X_2 \sim N(0,5)$.

4.5 Case study

4.5.1 Introduction of YRD

The Yellow River Delta (*N37º40´- N38º10´, E118º41´- E119º16´*) is the biggest alluvial plain in China and one of the youngest in the world, located in the coastal area of the Yellow River drainage basin in the east China. The main area of the YRD is located in the Dongying municipality. It includes five districts (Hekou, Lijin, Kenli, Dongying and Guangrao) and the wetlands (Figure 4.3). It has an area of about 6000 km^2. The Yellow River Delta includes urban areas, agriculture, fishing, natural reserve and holds economic importance for its oil and gas production.

The available water resources in the YRD are limited due to the polluted local surface water and salinized groundwater. About 90% of water use is provided by the Yellow River. However, between 1995 to 1998, the lower Yellow River was dry more than 120 days every year, up to 200 days in 1997. The zero-flow conditions have stopped since the Xiaoliangdi dam was put into operation in 2000. In recent years, a sharp decrease of water availability in the dry season occurred in the lower Yellow River caused by the rapid increase of water consumption in the Yellow River Basin area.

On the other hand, water demand in the Yellow River Delta is increasing with population growth, agricultural expansion and industry development. There is severe competition between different sectors for limited water resources in the YRD, especially between agriculture and industry. Although farms are small-scale, and agricultural productivity is low, agriculture uses a substantial part of the available water in periods of low river flow (Deltares 2009). The industry water reuse efficiency is relatively low (0.63) in the Yellow River Delta, and the industry is likely to consume more water as it continues to develop.

Therefore, to develop scenarios about the water demand will be crucial for better allocation of limited water resources and development of water management strategies for alleviating water stress, while maintaining socio-economic development.

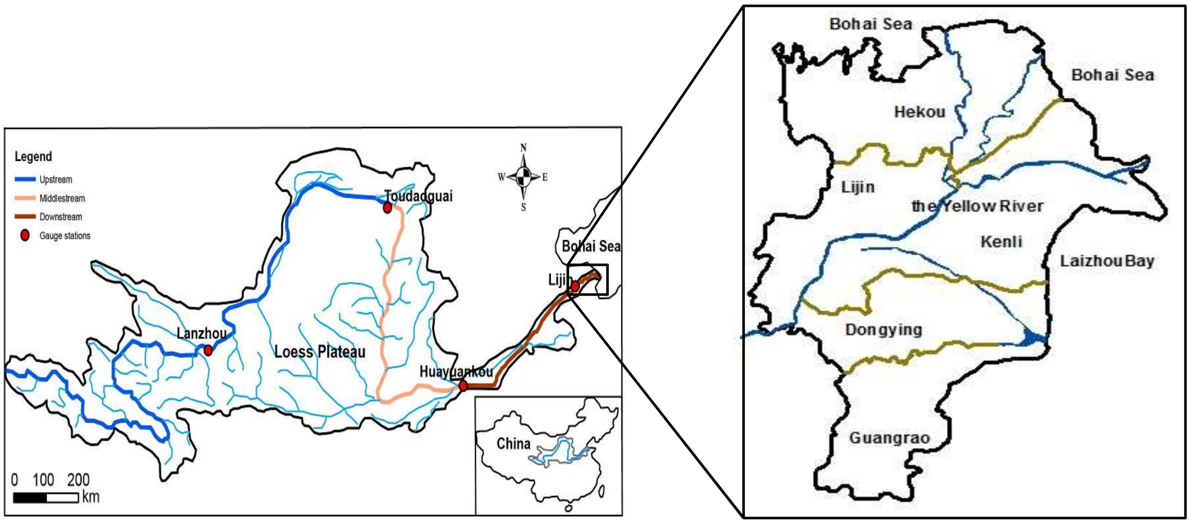


Figure 4.3 Location and five districts of the Yellow River Delta

4.5.2 Narrative Scenarios of future water demand

Narrative scenarios are storylines used to qualitatively describe the future states or development of the event. Water demand scenarios were developed using the GBN (Global Business Network) matrix analysis. The GBN matrix technique emerged with publication of the well-known future explorative book ‘ The Art of the long view ‘ written by (Schwartz 1991). The GBN matrix is constructed based on two dimensions of uncertainty with polarized values, which defines four domains with combined values from each uncertainty dimension. In each domain, storylines can be fleshed out and elaborated to describe the uncertainties. To construct the matrix, the two most important uncertainties need to be identified.

Scenarios of water demand are projections of the amount of water that would be generated in certain socio-economic and water use conditions, assuming unconstrained water supply (Groves

2006). Socio-economic factors such as population growth, economic development, agricultural patterns, water use styles, technologic innovation, and water policy are main drivers of future water demand projections. Water use pattern is believed to be the most important factor that influences future water demand (2030WaterResourcesGroup 2009). As agriculture is the biggest water user, it matters whether the industry or agriculture dominates the socio-economic development. Two important components of water use are from agriculture and industry, therefore, two dimensions of main uncertainties are picked up to construct the water demand scenarios, which are water use entities (industry/agriculture) and water use patterns (water-saving/ water consumptive). In each domain formulated by two extremes, a storyline can be constructed to describe the development of main driving forces (variables) (Figure 4.4).

Urbanization speed-up/water saving: Urbanization will speed up with more urban citizens and more land for urbanization purpose than agricultural expansion. Population in urban area increase larger than that in rural area, and more people emigrate from rural area into cities. Economy will maintain its fast growth, and agriculture become less intensive. Environment protection is important for quality of life. Water-saving policy helps to change social water use patterns. Environment is important in the water-saving society. The water use efficiency will be improved in both industry and agriculture.

Urbanization speed-up/water consumptive: Urbanization would develop as the case described above, and the priority is put in the industry instead of agriculture. From the institution level, water saving policy and technology is not improved. From the individual level, people don't have much awareness of water saving. So the water use patterns and water use efficiency are hardly improved.

Agriculture intensive/ water-saving: Agriculture remains the main socio-economic activity, and more uncultivated land is changed into farmland than for urbanization. The rural population keeps on increasing and less immigration activities will happen. Economy growth slows down. Irrigation remains the biggest water user, and its demand for water keeps on increasing as there will be more agriculture. People have more awareness of water saving and environment protection. Water-saving policy encourages farms and industry to improve water use efficiency.

Agriculture intensive/ water-consumptive: Agriculture is important for the local people and economy as described in the third scenario. As described in the second scenario, the agriculture and industry water consumption is not encouraged to be improved.

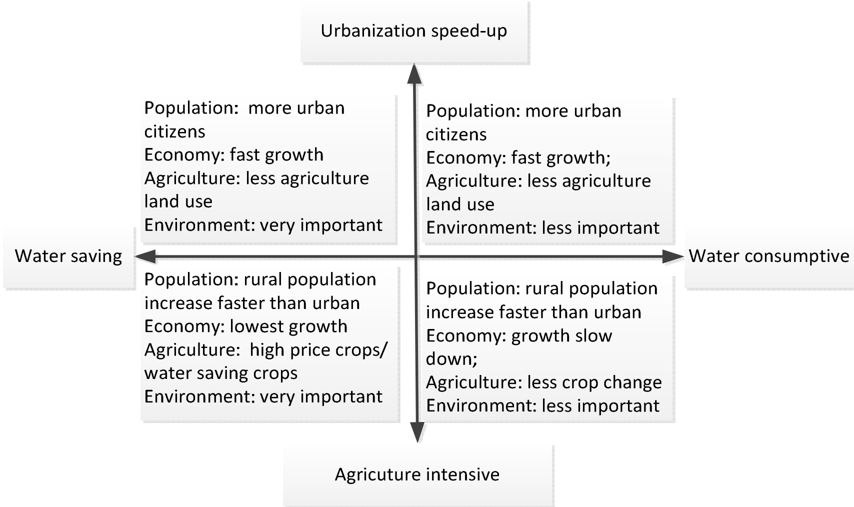


Figure 4.4 GBN matrix of water demand scenarios.

4.5.3 Water Demand Model

Three main attitudes of water demand were summarized by (Hoekstra 1998): a given need which should be satisfied, a necessity only to be met for 'basic needs' such as drinking water, an economic good subject to the price charged. This work adopts the first view of water demand to support population, agriculture, industries and ecosystem. A large number of water demand models exist in the literature. Three important criteria can be used to select a proper model to forecast socio-economic water demand: planning objective, available data and available resources. Generally, four methodologies to forecast water demand are trend extrapolation, per capita method, number of unit times a fixed per unit use method, and number of unit times a variable per unit use method (Davis 2003). From the data collecting point of view, more complex model will require more detailed and various data. According to the available data and discussion with the experts, a relatively simple and general model based on the number of unit times per unit use method was used by aggregating water requirement from the end users (e.g., people, crops, livestock, and industry). The model is well suited to project future water demand straightforwardly, by considering how the change of the scale or production of water user and their average water use intensity will impact future demand. Figure 4.5 demonstrates the components that influence water demand. Water demand in the Yellow River Delta include mainly four users: domestic water demand, industry water demand, agriculture water demand and environment water demand. Among them, agriculture was the biggest water user, consuming more than 80% of the total water use. Total water demand $W_{tot,y}$ in the year y is the sum of water requirement of the four sectors in the same year:

$$W_{tot,y} = W_{dom,y} + W_{ind,y} + W_{agr,y} + W_{env,y} \quad (4.17)$$

Where $W_{dom,y}$ is the domestic water demand in year *y*; $W_{ind,y}$ is the industry water demand in year *y*; $W_{agr,y}$ is the agricultural water demand in year *y*; $W_{env,y}$ is the environment water demand in year *y*.

Domestic water demand: Domestic water demand includes water required for household in rural and urban area. It is principally dependent on per capita water consumption, population growth, water use efficiency, and water price elasticity. The impact of price elasticity on water demand is not considered in the estimation of domestic water demand, due to relatively low and stable historical water prices.

$$W_{dom,y} = \sum_I Pop_{i,y} \cdot I_{dom,i,y} \quad i=1,2 \quad (4.18)$$

Where $Pop_{i,y}$ is the population in rural area (*i*=1) and urban area (*i*=2) in year y, $I_{dom,i,y}$ is the corresponding average per capita water consumption.

Industry water demand: Industry water demand is impacted by industry production, marginal productivity of water, industry water use efficiency, water price, and water production elasticity. In the YRD, industry water users mainly include water for production, architecture and tertiary business. In the Cobb-Douglas production function, the water demand for production is a function of marginal productivity of water $\rho_{ind,j,y}$ (\$/m^3), total production $Prd_{j,y}$ (\$), and production elasticity of water σ .The index *j* represents industry, architect and tertiary departments.

$$W_{ind,y} = \sum_J \sigma \cdot Prd_{j,y}/\rho_{ind,j,y} \quad (4.19)$$

However, the industry production elasticity of water is difficult to estimate when the historical data on capital, labor, and energy is hard to collect. Therefore, the industry water demand is simplified as the water withdrawn per unit industrial production $I_{ind,j,y}$ (m^3/\$) multiplied by total production $Prd_{j,y}$ (\$).

$$W_{ind,y} = \sum_J Prd_{j,y} \cdot I_{ind,j,y} \quad j=1,2,3 \quad (4.20)$$

Agriculture water demand: Irrigation water consumption for crops such as wheat, soybean, cotton and rice contributes more than 90% of water use in the agriculture sector. The rest of water is provided to orchard, fishing and livestock. Irrigation water demand is determined by crop types, crop areas, climatic conditions, irrigation efficiency, etc. Agriculture water demand $W_{agr,y}$

is computed as the crop area $Area_{k,y}$multiplied by average water use intensity $I_{agr,k,y}$, taking into account the agricultural water use efficiency $eff_{k,y}$. k is different crop types.

$$W_{agr,y} = \sum_k \frac{Area_{k,y} \cdot I_{agr,k,y}}{eff_{k,y}} \tag{4.21}$$

Environment water demand includes the wetland water demand in the estuary and the out-stream ecological water use in the YRD municipality in the study. The objective of sufficient water for a healthy ecological system was not always met, as minimal weight was put on the environment in the past. For example, the out-stream water use holds only 2% of total water demand in the YRD in the last 10 years. Therefore, the objective of environment water prediction is to improve the health of the ecological system by meeting the minimal water requirement for the wetland ecological system and to maintain or improve the out-stream municipality environmental water conditions in the YRD. According to estimates, the minimal water demand to keep healthy wetland ecology is about 0.686km3 (Li, Fan et al. 2011). In this study, wetland water demand will be met at the minimal level, and the out-stream municipality environmental water demand will be changed corresponding to the weight put on the environment. The water demand prediction will only include the out-stream water demand. It was simplified by modelling the growth rate r_{env}. The range of growth rates is [0-4%], considering the different importance levels of the environment in society based on the scenarios. A uniform distribution was assigned to it.

$$W_{env,y+t} = W_{env,y} \times (1 + r_{env})^t \tag{4.22}$$

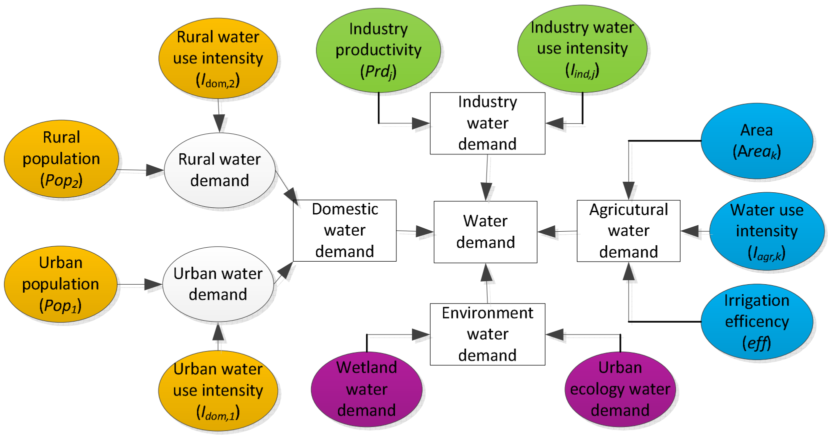


Figure 4.5 Components of water demand. The variables in colored box will be quantified based on scenarios, and variables with the same color are considered as a group.

4.5.4 Future water demand projection

To project water demand of domestic, industrial and agricultural sectors, the number of water use units and the per unit use values change each year, as quantified by a growth rate r. Therefore, the projection of future water demand depends on the growth rate in the predicted period. Future water demand is influenced by a variety of variables, such as socio-economic development, population growth, climate conditions, life quality, water use efficiency, water saving technology, etc.. These variables thus also affect the growth rate. However, future states of these variables are uncertain, leading to difficulty in quantifying the growth rate. Another difficulty is that some of these growth rates are definitely interrelated, and the dependence level will impact the final outcomes. Therefore, it is necessary to model the dependence structure by considering the joint multivariate distributions.

To take into account the two difficulties, two steps are required to quantify the growth rate and model the future water demand probabilistically to cope with uncertainty:

(1) Assign marginal probability distributions $g_i(r_i)$ to variables of interest, i.e. the annual growth rates. Scenario-based expert elicitation was applied to quantify the variables probabilistically under uncertainty, considering that historical data is not available. Scenarios of water demand were developed to articulate future thinking into storylines and explore possible tracks of the variables. On the basis of the storylines, probability distributions of the growth rates were elicited using expert judgement using the SHELF procedure.

(2) Construct joint distributions among these variables if they are dependent, $f(r_1, r_2, \cdots, r_n|R)$ and sample from the multivariate distribution and propagate the uncertainties to the outcome using Monte Carlo simulations. In modelling future water demand, the dependence of variables were taken into account using the Gaussian Copula considering the high dimensionality of the problem.

The process can be formulated using Bayesian inference in the following way:

$$f(W_{tot}, r_1, r_2, \cdots, r_n|R) \propto f(W_{tot}|r_1, r_2, \cdots, r_n, R) f(r_1, r_2, \cdots, r_n|R); \quad (4.23)$$

And the multivariate joint probability distribution can be written as:

$$f(r_1, r_2, \cdots, r_n|R) = g_1(r_1) g_2(r_2) \cdots g_n(r_n) \times c_n^{Gauss};$$

$$c_n^{Gauss} = \exp(-\frac{V^T(R^{-1}-I)V}{2}) / |R|^{1/2} \quad (4.24)$$

Where c_n^{Gauss} is the n-dimensional Gaussian copula, R is the Pearson's correlation matrix, I is the $n \times n$ identity matrix, $g_i(r_i)$ is the marginal density distribution of r_i, V is vector of variables coming from the specific marginal distributions and the correlations.

The correlation matrix R contains correlation coefficients between different growth rates. To decrease the number of parameters to be estimated, the variables are divided into three groups to model domestic, industrial and agricultural water demand, respectively (variables in yellow, green and blue colour in Figure 4.5). And the variables are assumed to be independent with the ones in other groups. Therefore, the process can be split into three segments and written as:

$$f(W_{tot}, r_1, r_2, \cdots, r_n|R) \propto f(W_{dom}|r_{11}, \cdots, r_{1q}) f(r_{11}, \cdots, r_{1q}|R_1) \dots$$
$$\times f(W_{ind}|r_{21}, \cdots, r_{2j}) f(r_{21}, \cdots, r_{2j}|R_2) \times f(W_{agr}|r_{31}, \cdots, r_{3k}) f(r_{31}, \cdots, r_{k3}|R_3); \qquad (4.25)$$

With:

$$f(r_{i1}, \cdots, r_{i(q/j/k)}|R_i) = g_{i1}(r_{i1}) \cdots g_{i(q/j/k)}(r_{i(q/j/k)}) \times c_i; \qquad i = 1,2,3, \; q + j + k = n$$
$$c_i = \frac{\exp\left(-\frac{V^T(R_i{}^{-1} - I)V}{2}\right)}{|R_i|^{\frac{1}{2}}} \qquad (4.26)$$

Where $R_1\,(r_{11}, \cdots, r_{1q})$, $R_2\,(r_{21}, \cdots, r_{2j})$, $R_3(r_{31}, \cdots, r_{3k})$ are the correlation coefficients of variables in three groups, respectively, $g_i(r_i)$ is the marginal density distribution of r_i ($i =$ 1,2,3), $c_{i(q/j/k)}^{Gauss}$ is the $q\ or\ j\ or\ k$-dimensional Gaussian copula, I is the identity matrix of size $q\ or\ j\ or\ k$, and V is a vector of variables coming from the specific marginal distributions and the correlations.

4.5.5 Results

4.5.5.1 Marginal probability distribution assessment

The quartile probability assessment of each variable from the three experts is shown in appendix A. A plausible range of each variable is first required to be decided. According to the SHELF procedure, the lower and upper bounds are the same for all experts. The range of the variable is a joint decision of the experts, so that they all believe that the variable is extremely unlikely to be located outside this range. The identification of the 50% quartile is relatively simple, and the 25% and 75% quartiles are obtained by anchoring the bounds and the median values. After eliciting all values, experts should check if the range of four intervals (lower bound ~ 25% quartile, 25% ~50% quartile, 50% ~75% quartile, 75% quartile ~ the upper bound) is equally likely. From the elicitation table, experts were very diverse in the opinions of most variables, and agree in some variables such as grass and fishing area growth rate.

Appendix B gives an example of how to fit the distribution of urban population growth rate to the quartile estimation using SHELF software. Each figure shows the value of three quartiles and the density function. A normal distribution was fit to the variable based on each expert's judgement, and the figure in the right-bottom shows the mixed distribution based on the average value of quartiles estimated by experts. As shown in the figure, the values of 25% and 75% quartiles of the fitted distribution do not perfectly match the estimation. In order to check the goodness of fit of the distributions, the estimated quartile values and the same quartile from the fitted distributions are plotted. Figure 4.6 shows that the estimated quartile values matches well with values of the same quartile from the fitted distributions. It shows that the fitted distributions can represent the experts' judgement.

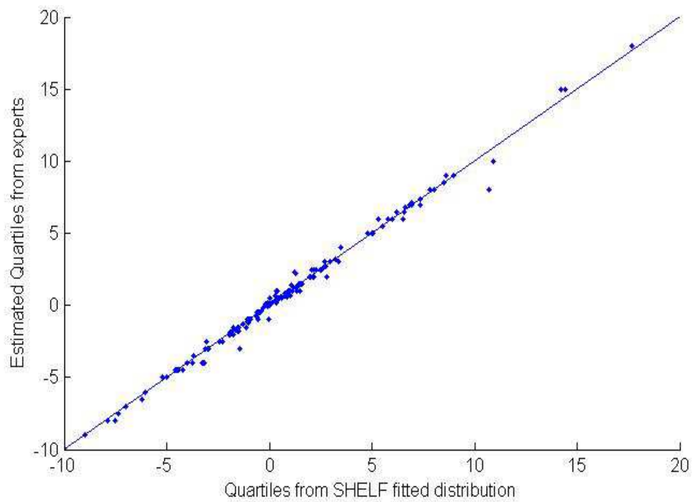


Figure 4.6 Estimated quartile values and values from the fitted distribution.

Appendix C demonstrates the fitted priors based on three experts' judgement and the posteriors using the linear pooling approach. Normal distributions were fit to represent the uncertainty of variables. According to (Clemen and Winkler 1999), simple combination rules such as a simple average tends to perform quite well although it considers no dependence between experts. However, complex models such as normal model and copula models are quite sensitive to the dependence, leading to poor performance in some cases (Jouini and Clemen 1996). Therefore, the simple aggregating method, *Linear opinion pooling,* was applied to combine the experts' opinions into a single probability distribution. We assumed experts to be equally qualified and gave them equal weights. The simple equal-weight method produces multi-modal probability distributions when the opinions of experts are diverse, for instance, the posterior densities of rural water use intensity growth rate, orchard area growth rate and so on. The multi-modal densities allow the co-existence of the heterogeneity of experts' opinions.

4.5.5.2 Multivariate probability distribution analysis

The variables are likely to be dependent, and the dependence level will impact the final outcome. In order to consider their dependency, a multivariate distribution was constructed on the basis of the marginal distributions and Gaussian Copula function.

The important step is to identify the correlation coefficient among the variables. Unsurprisingly, there is no way to get the accurate correlation between variables, especially since the data is not available. Therefore, the information provided by people who have local and statistical knowledge with correlation becomes valuable. The correlation matrix was estimated by consulting seven Chinese PhD researchers in the Water Management Group at TU Delft. They first received statistical knowledge about the Pearson's correlation coefficient, and were given several scatterplots to train their judgement about the strength of correlation between a pair of variables. The correlation was judged separately at first, and the final outcome was refined after discussions. The result is listed in Appendix D.

Markov Chain Monte Carlo (*MCMC*) was used to sample from the Gaussian copula-based multivariate joint distributions. The simulations were run 10,000 times for each group of distributions, and the first half of the samples were removed as burn-in. As an example, figure 4.7 shows the multivariate distribution samples of r.pop1, r.pop2, r.Idom1, based on Gaussian Copula $\rho1 = -0.8$, $\rho2 = -0.45$, $\rho3 = [1 - 0.8 - 0.45; -0.8\ 1\ 0; -0.45\ 0\ 1]$, with marginal probability distributions of *r.pop1, r.pop2, r.Ipop1*.The samples from the Gaussian copula-based bivariate/multivariate distributions are symmetric around the central points.

Figure 4.8 shows 50 samples from the multivariate distributions of variables of domestic, industrial and agricultural water demand separately. As a Gaussian copula considers weak tail dependencies and no dependence is considered at the extremes, the samples were mainly distributed in the central part of the marginal distributions. In the graph, the samples which are distributed with opposite bounds such as variables 2, 4, 14, 17, 18, 19, clearly demonstrate the bimodal marginal distributions.

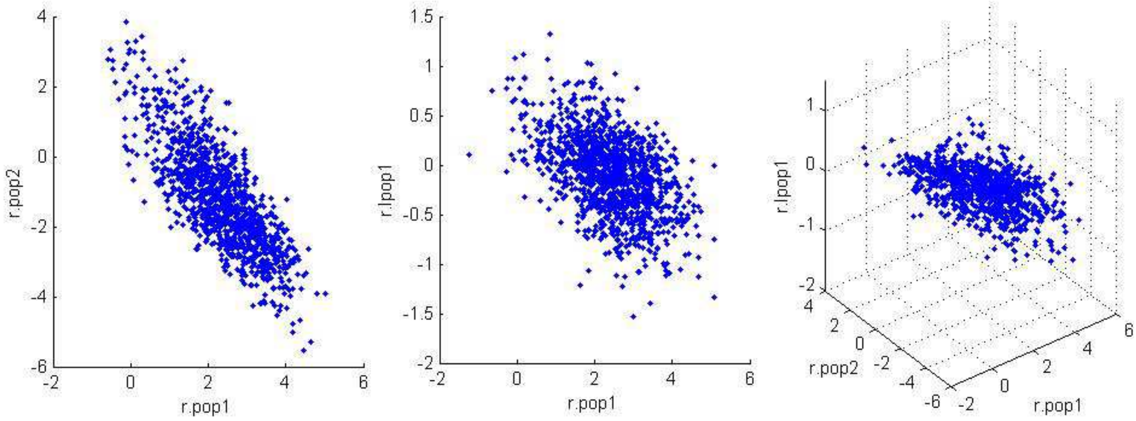


Figure 4.7 Multivariate distribution samples, Gaussian copula $\rho1 = -0.8$, $\rho2 = -0.45$, $\rho3 = [1 - 0.8 - 0.45;\ -0.8\ 1\ 0;\ -0.45\ 0\ 1]$, with marginal probability distributions of *r.pop1, r.pop2, r.Ipop1*.

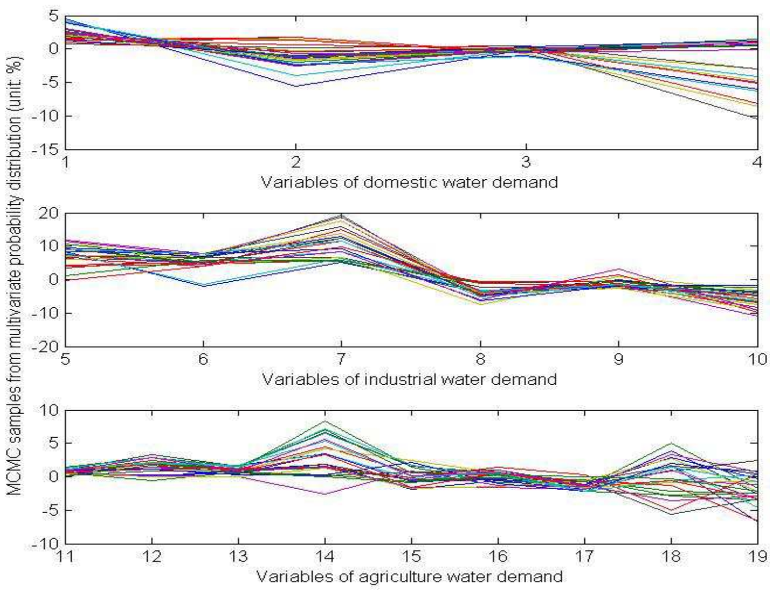


Figure 4.8 *MCMC* samples of variables from Gaussian Copula-based multivariate distributions.

4.5.5.3 Future water demand

In this section, future water demand until 2039 is predicted according to the results from the scenario-based expert elicitation and the Gaussian Copula-based model when dependence among variables is considered. *MCMC* samples from the multivariate probability distribution were applied as input to the water demand models. However, the autocorrelation of the driving variables are not taken into account. Figure 4.9 and 4.10 shows the future water demand without and with considering the dependence. The uncertainty band of water demand is smaller with considering the dependence of the variables, as the samples from the joint Guess-copula distributions are more centralized compared with the samples from marginal distributions separately. In the following analysis, the future water demand focuses on the results of the Gaussian copula-based model.

Water demand consists of four main sectors: domestic, industrial, agricultural and environmental water sectors. The 99% quartile and the probability distribution of annual water demand of the four sectors are presented in Figure 4.10. The 50% percentile of water demand, seen as the medium of water demand, in all sectors tend to increase, as the distribution of water demand mainly locates on the right side of the value in the base year. The 0.5% percentile represents the scenarios of water-saving society and slow growth in both industry and agriculture in the YRD. It shows decreases in domestic/ industrial water demand for a short period and a constant decrease in the agricultural water demand, which is consistent with the probability distributions shown in the figure below. The 99.5% percentile mainly represents the water-consumption behaviour and rapid growth in both agriculture and industry in the YRD. It shows a yearly increasing trend for all the sectors. The shapes of 0.5% and 99.5% percentiles are slightly symmetric around the 50% percentile, which reflects the symmetric structure about the centre point in the Gaussian copula (excluding environmental sector). The change of total water demand combines the change of the four sectors, which follows the shape of the former three sectors since they contribute about 95% of total water demand. The uncertainty of water demand in the future is increasing due to the wider band of the 99% confidence interval. Overall, future water demand has an increasing trend in the long term. If no water management strategies are planned and adopted, the water shortage problem is likely to become worse in the future.

Table 4.1 shows the three percentiles of water demand every 5 years and the change compared with the base year 2010. The water demand is increasing every 5 years. The order of water demand from different sectors remains the same, and they are agriculture, industry, domestic and environment. Although the agriculture is still the biggest water user in the YRD, industrial water demand has a bigger increment than that of agriculture, which is consistent with the assumption made by the experts that the urbanization speed-up is more likely than the agricultural intensive scenario (*r.prd1*, *r.prd2*, *r.prd3* in Appendix A).

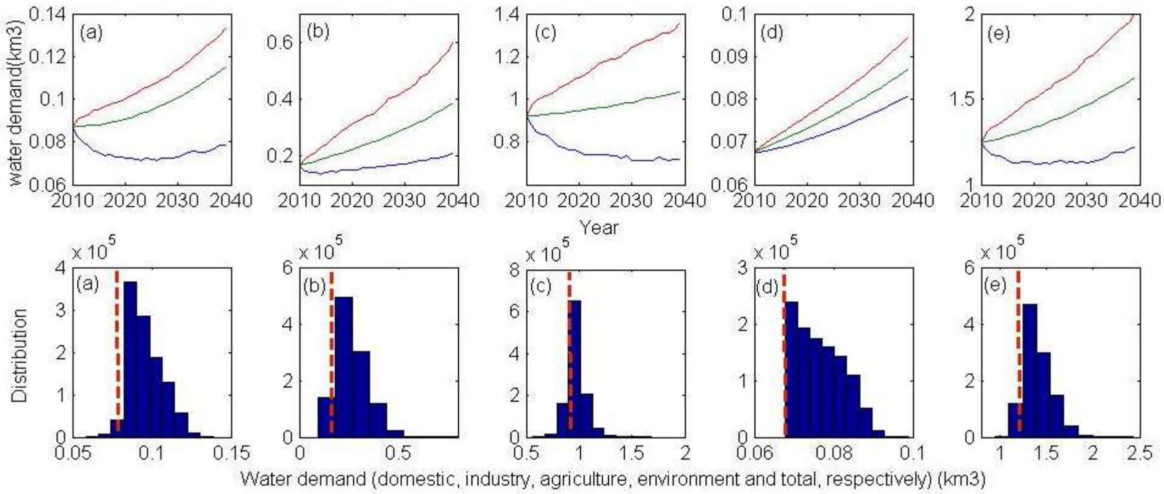


Figure 4.9 0.5%, 50% and 99.5% percentile and probability distribution of annual water demand between 2010- 2039 when variables are considered independently. (a) domestic water demand, (b)industrial water demand,(c)agricultural water demand,(d) out-stream environmental water demand, (e) total water demand. The red broken line is water use in 2010

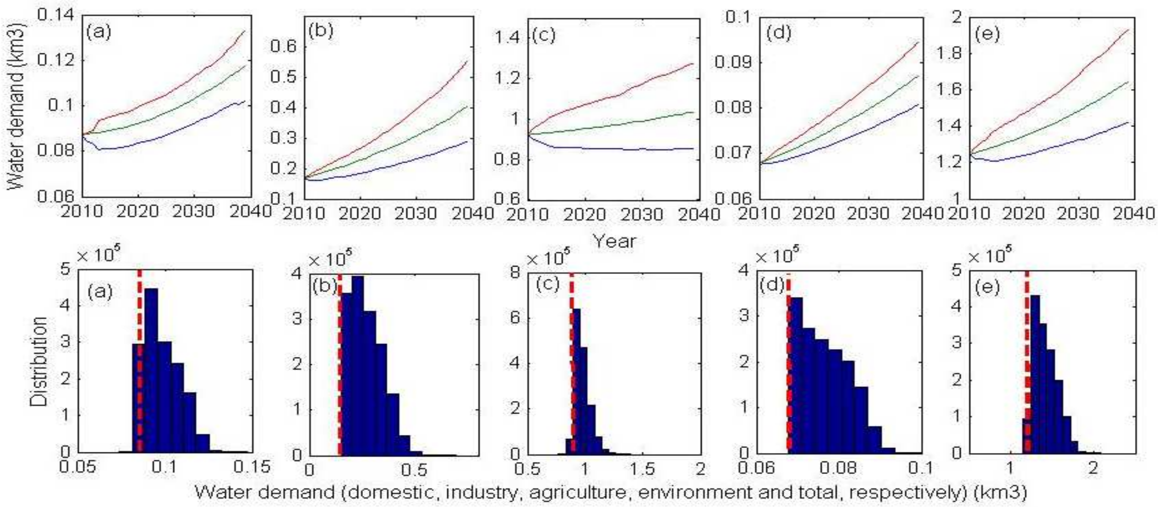


Figure 4.10 0.5%, 50% and 99.5% percentile and probability distribution of annual water demand between 2010-2039 when variables are considered dependently. (a) domestic water demand, (b) industrial water demand,(c) agricultural water demand,(d) out-stream environmental water demand, (e) total water demand. The red broken line is water use in 2010

Table 4.1 0.5%, 50% and 99.5% percentiles of water demand (km^3)

Year	Percentile	Domestic (a)	Industrial (b)	Agricultural(c)	Environmental (d)	Total (e)
2010		0.0869	0.1676	0.9231	0.0677	1.2453
2015	0.5%	0.0809 (-6.84)	0.1682 (0.39)	0.8611(-6.7)	0.0685 (1.32)	1.1789 (-5.32)
	50%	0.0888 (2.26)	0.1956 (16.71)	0.9364 (1.45)	0.0702 (3.82)	1.2912 (3.69)
	99.5%	0.0948 (9.12)	0.2186 (30.45)	1.0220 (10.72)	0.0720 (6.45)	1.4075 (13.03)
2020	0.5%	0.0833 (-4.07)	0.1850 (10.43)	0.8555 (-7.3)	0.0705 (4.18)	1.1945 (-4.07)
	50%	0.0921 (6.04)	0.2277 (35.86)	0.9525 (3.20)	0.0731 (8.05)	1.3456 (8.06)
	99.5%	0.0992 (14.26)	0.2674 (59.59)	1.0695 (15.87)	0.0760 (12.28)	1.5124 (21.45)
2025	0.5%	0.0871 (0.25)	0.2067 (23.34)	0.8547 (-7.4)	0.0727 (7.52)	1.2214 (-1.91)
	50%	0.0968 (11.44)	0.2645 (57.86)	0.9666 (4.72)	0.0763 (12.72)	1.4044 (12.77)
	99.5%	0.1049 (20.73)	0.3261 (94.57)	1.1054 (19.75)	0.0802 (18.54)	1.6167 (29.82)
2030	0.5%	0.0921(6.09)	0.2308 (37.75)	0.8527 (-7.61)	0.0753 (11.28)	1.2512 (0.47)
	50%	0.1030 (18.53)	0.3076 (83.57)	0.9904 (7.29)	0.0797 (17.85)	1.4809 (18.92)
	99.5%	0.1127 (29.70)	0.3949 (135.63)	1.1718 (26.94)	0.0848 (25.36)	1.7643 (41.68)
2035	0.5%	0.0985 (13.37)	0.2616 (56.12)	0.8499 (-7.92)	0.0781 (15.51)	1.2883 (3.45)
	50%	0.1106 (27.32)	0.3569 (112.95)	1.0155 (10.01)	0.0836 (23.55)	1.5666 (25.81)
	99.5%	0.1219 (40.34)	0.4745 (183.16)	1.2282(33.06)	0.0899 (32.82)	1.9147 (53.75)

Note: the numbers in parentheses are the percentages of change compared to water demand in 2010 (%).

4.6 Discussions and Conclusion

4.6.1 Scenario-based expert elicitation under uncertainty

Scenario-based expert elicitation provides a feasible framework to incorporate experts' opinions regarding uncertainty to project future states, as data-based approaches are not feasible due to the data scarcity. Scenarios articulate the mental models in the manner of storylines, and numerical information can then be added to model the future states quantitatively on the basis of the stories. Scenarios attached with probabilities are believed to be more realistic as the future states would not be equally likely, and they allow scenario developers to quantify their assumptions explicitly. To quantify the scenarios, expert elicitation was largely researched and used considering data limitations. In the study, scenario-based expert elicitation assessed the probability distributions, and allows the projection of future water demand stochastically.

Expert elicitation is scientifically sound when it is credible, transparent and repeatable. To this end, the well-structured SHELF procedure provides a comprehensive and repeatable procedure to incorporate experts' knowledge as input to model future water demand. The graphical interface enabled experts to visualize their assessment of probability distributions, and give immediate feedback and adjustment of their judgement. However, two important issues need to be addressed before starting the expert elicitation process: (1) selection and training of experts has to be done carefully before their judgement can be used to support decision making; (2) the calibration of experts' ability to express their knowledge is useful to validate their judgement. In the study, the training of experts' judgement in the probabilistic way was carried out, but the performance of experts' judgement was not formally calibrated and distinguished. However, the SHELF allowed the elicitation process to receive immediate and frequent feedback from the experts, which tends to calibrate the expert judgement to be consistent with his knowledge. In order to keep the process transparent, the elicitation process should be well recorded.

4.6.2 Mathematical methods of aggregating probability distribution need to be improved

Three experts were interviewed and consulted for the assessment of probability distributions. The aggregated probability distribution assessed by the three experts was valuable for capturing the accumulative information about experts' opinions regarding uncertainty. The simple linear pooling method was implemented for this purpose. The linear pooling method allows the assignment of different weights to experts, and the expert who is believed to give better judgement would receive more weight. The knowledge level and ability to provide probability assessment were regarded equally qualified as their judgement were ensured by iterative adjustment and correction with SHELF. It is believed that " the simple rule will always play an important role due to their ease of use, robust performance and defensibility in public policy "(Clemen and Winkler 1999). As far as more complex mathematical models, the Bayesian aggregation rules are powerful and growing rapidly. It considers the dependence among experts, and allows for updating the expert's beliefs. However, constructing the likelihood functions to model the dependence and the biases of experts is difficult and subtle, yet it directly determines the quality of the aggregated probability distributions. Further studies are required to better understand the behaviour and the full potential of Bayesian rules to facilitate the assessment and aggregation (Chhibber, Apostolakis et al. 1992). Another issue about the aggregation of multiple probability distributions is that the single aggregated one is actually not the judgement from any expert. It means that experts have to negotiate or compromise in order to reach a consensus, or more research has to be done to develop better mathematical combination rules and behaviour aggregation procedures to improve the performance.

4.6.3 Copula-based multivariate probability distributions

In this study, dependence among water variables to model water demand is considered and copula-based model was used to construct multivariate probability distributions. Copula theory has become popular in economic and financial models to account for the dependence between multiple variables; similarly, its application in water resources management should be also promising as the different driving forces of water events are interdependent. Copula-based models provide explicit tools to construct multivariate probability distributions, and the copula function is independent from the marginal distributions, which makes the approach flexible. This study assumed multivariate normal distribution among multiple variables, and investigated the Gaussian copula, which is more tractable for high dimensions. The comparison and application of various bivariate-copula could be also interesting, and has been discussed by (Bhat and Eluru 2009). Three steps are required to construct copula-based multivariate probability distribution: first, the marginal probability distributions have to be specified for each variable, and this can be done with the techniques of data-based estimation or expert elicitation; then the dependence of the variables has to be quantified with the Pearson's moment correlation, rank-order correlations Spearman's ρ_s or Kendall's τ; last step is to identify the copula to join the marginal distributions into a multivariate distribution. One challenge of the copula-based model is to extend the copula function into higher dimension, as the correlations matrix becomes larger with higher dimension. More effort to estimate the correlations and expensive computation will be required.

4.6.4 Water demand projection in the YRD

Future water demand in the Yellow River Delta is difficult to project as the driving forces such as population growth, water use patterns, water policy are unknown, and the past data is not adequate to estimate the trend of development in this study. Scenarios are powerful tools to create pathways of their development, and probabilistic information is helpful to quantify the uncertainty. A GBN matrix outlined the water demand scenarios including main uncertainties, and storylines were elaborated to flesh out four scenarios. However, not only four pathways were quantified based on each scenario, but also the possible situations between each scenario were taken into account. Indeed, it is difficult to match the quantitative pathway with the scenarios specifically, but the probability distribution includes the plausible range of futures covered by the four scenarios as well as the futures between them. Additionally, the probabilistic information was propagated to yield probabilistic water demand scenarios.

Water demand is likely to increase in the long run, and the lower and upper bound of the uncertainty band represent two extremes: water saving society together with slow growth of urbanization and agriculture, which approaches the centre of the GBN matrix; water consumption society with rapid growth of urbanization and agriculture, which approaches the extremes of the matrix. Values between the bounds represent the possible futures between the extreme scenarios. As the urbanization speed-up scenarios are assumed to be more likely than agricultural society, the industrial water demand has a bigger increment compared with that of agricultural water demand. If no water management strategies are adopted, the water shortage situation is likely to become more severe.

In summary, the paper presented a scenario-based expert elicitation method and copula-based multivariate analysis to explore future water demand under uncertainty. In water resources planning and management, the information from experts with special knowledge and experience is valuable as input for modelling and decision making, although there are quite some challenges in evaluating the credibility and reliability of the obtained information. Therefore, to explore the full potential of information from experts, it is important to develop scientifically sound mathematical and behaviour approaches to make good use of this information. This study employed well-structured expert elicitation procedure and mathematical approaches, taking into account the credibility, availability and feasibility of these approaches. The water demand projections are supposed to facilitate the decision making process in water resources planning and management, will be used in Chapter 6 for a decision making case study in the Yellow River Delta, China.

Chapter 5 Probabilistic scenario-based decision making framework for water resources planning and management

5.1 Introduction

Decision making under uncertainty refers to the act of choosing one decision among two or more decision alternatives when the outcomes of those alternatives are uncertain (Schultz, Mitchell et al. 2010). Uncertainty in decision making exists due to the deficiencies in knowledge about the past, present and future states of the system to be managed, and the ambiguities in perceiving consequences of decision alternatives in the decision-making process. In addition, decision making uncertainty exists in practical decision making activities due to the diverse social objectives, interests and backgrounds of different stakeholders and decision makers. Accounting for uncertainty in decision making, it is necessary to analyze potential risks and to hedge decisions away from large losses (Reckhow 1994).

Decision analysis has been applied to assist making decisions in the face of uncertainty. It starts from framing the decision problem, going through the process of analyzing uncertainty, modeling decision alternatives and assessing decision performance, communicating uncertainty and risk to decision makers, and eventually helping them to make decisions in a consistent and rational way. Schultz (Schultz, Mitchell et al. 2010) pointed out that the main part of decision analysis is to structure decision models incorporating uncertainties, identify the consequences of decision alternatives and incorporate decision makers' preferences. A set of ideas and analytical models has been developed to manage uncertainties for decision analysis, such as event trees and Bayesian Belief Networks for probabilistic inference and uncertainty propagation (Huang, Chen et al. 2001, Robertson and Wang 2004, Ames, Neilson et al. 2005), decision trees, influence diagrams and scenario development for modeling and exploring uncertain events and the decision outcomes (Peterman and Anderson 1999, von Winterfeldt and Edwards 2007, Mahmoud 2008). Another crucial task for decision analysis is to rank decision alternatives under uncertainty for choosing the final decision. A set of decision rules has been developed and adopted to rank decision alternatives according to their consequences against uncertainties and the preference of decision makers (Tung, Wang et al. 1993, Reda and Beck 1997, Xu and Booij 2004, Xu and Tung 2009). However, the presence of uncertainty in the consequences and decision makers' preference complicate the selection of an appropriate decision rule. Most of decision rules focus on the stochastic consequences and decision makers' preference on wealth (risk-neutral decision makers), while ignoring the case that decision makers are usually not risk neutral but risk averse or risk seeking when making decisions in face of uncertainty. Utility functions that incorporate decision makers' preference and risk attitudes are useful to understand such influences on the final choice of alternatives (Schultz, Mitchell et al. 2010).

A well-structured decision making framework is essential to support and guide decision analysis in face of uncertainty. A number of decision making frameworks have been developed and adopted in water resources planning and management (Stewart and Scott 1995, Duchness, Beck et al. 2001, Groves 2006, Xu, Tung et al. 2009, Lempert and Groves 2010, Vucetic and Simonovic 2011). Means III et al. (2010) (Means III, Laugier et al. 2010) reviewed and compared five decision making frameworks incorporating uncertainties, namely classic decision making method, traditional scenario planning, robust decision making, real options and portfolio planning. Here, we will compare the first three methodologies. From the perspective of uncertainty management, classic decision making applies probabilities to characterize uncertainties and identifies the optimal decision against the most likely scenarios. Therefore, the outcome of decision making will be sensitive to identification of the most likely scenarios, and be vulnerable to surprises or unexpected events in the future (Lempert, Groves et al. 2006). The traditional scenario planning and robust decision making abandon probabilistic information, and identify the robust decision over a wide range of scenarios. However, the lack of probabilistic information makes it impossible to quantify the risk that decision alternatives may cause, for example, the risk of economic losses, so that decision makers are ambiguous about the risk of choosing any alternative under uncertainty. On the other hand, it is likely to lead to arbitrary selection of scenarios and alternatives (Means III, Laugier et al. 2010). A framework to combine the probabilistic information and a large set of scenarios is more desirable to cope with uncertainties in decision making.

This chapter is organized as follows: firstly, the classic decision theory based on Expected Utility theory in face of uncertainty will be introduced briefly; secondly, three popular decision making frameworks in water resources planning and management, classic decision making, traditional scenario planning and robust decision making will be reviewed and compared, focusing on the difference of these frameworks, for example, the uncertainty management, the output presentation, the involvement of decision makers' preference and risk attitudes, etc.; thirdly, decision rules to rank decision alternatives in water resources management will be investigated and compared, in order to find an appropriate decision rule; lastly, a probabilistic scenario-based decision making framework will be proposed, trying to compensate for disadvantages of existing methods. The proposed framework provides a plausible approach to explicitly manage uncertainties, as well as inform the influence of decision makers' preference and risk attitudes on decision making.

5.2 Decision theory

Decision theory was developed to study the decision making problem when facing uncertain outcomes of choices. Going back to 1713, the conventional method is to choose a decision based on maximizing the expected value of outcomes. However, the idea was first challenged by the famous St. Petersburg Paradox. It was a coin-tossing game and the player invested money k to play with it. The gain will be doubled if a tail appears, and the player will lose everything (the gain would be 0) if a head appears. The payoff will be $\sum_{n=1}^{\infty}[(\frac{1}{2})^n \times 2^{(n-1)} \times k + (\frac{1}{2})^n \times 0]$, where n is number of coin tosses before head appears. The game would have infinite gain as the probability of tail and head is equal, and the player should enter the game based on the maximal expected gain. But the paradox is that most individuals are not willing to pay to enter the game. Daniel Bernoulli resolved the St. Petersburg Paradox in 1738 by introducing the value function to incorporate an individual's preference level on wealth, and demonstrated a diminishing marginal satisfaction associated with increasing wealth. An individual's preference to wealth is included in Bernoulli's value function, but the value function was not able to distinguish a sure thing and an uncertain alternative with identical expected outcomes. To address the issue, von Neumann and Morgenstern extended the theory by introducing expected utility theory to incorporate decision makers' preferences towards wealth and the corresponding risk under uncertainty. The preference among uncertain alternatives can be identified by knowing the utility of their outcomes and the probabilities. A set of axioms were developed to pursue rational decision making behavior under uncertainty (von Neumann and Morgenstern 1947). These axioms are:

(1) Completeness. The decision maker is unambiguous about his preference or can distinguish his preference against multiple alternatives. For two options, L and M

$$if\ u(L) < u(M), u(M) < u(L)\ \ or\ u(L) = u(M)$$

then $\mathrm{L} \prec \mathrm{M}, \mathrm{M} \prec \mathrm{L}$ or $\mathrm{L} \sim \mathrm{M}$ (either *M* is preferred, or *L* is preferred, or L indifferences *M*).

(2) Transitivity. It assumes the preference is consistent across any three options

$$\text{if } \mathrm{L} \prec \mathrm{M}, \mathrm{M} \prec \mathrm{N} \text{ then } \mathrm{L} \prec \mathrm{N}$$

(3) Continuity. It assumes a probability p exists so that decision makers' preference against the outcome of an uncertain alternative $(\mathrm{p}, L; 1-\mathrm{p}, N)$ is indifferent to the outcome of a certain option M. The outcome of the certain option is called the certainty equivalent of the uncertain option.

$$if\ L \prec M \prec N\ , there\ exist\ a\ probability\ p \subseteq [0,1],$$

$$p \cdot u(L) + (1-p) \cdot u(N) = u(M)$$

Then

$$pL + (1-p)N \sim M$$

(4) Independence. It assumes that a preference holds independently of the possibility of another outcome.

$$if\ L \prec M, then\ for\ any\ N\ and\ p \subseteq (0,1),$$

$$pL + (1-p)N \prec pM + (1-p)N$$

A utility is a dimensionless number to measure the worth, satisfaction, or preference on wealth that an individual has. A utility function $U(x)$ is a real mathematical function to convert value functions *V(x)* of an attribute set *X* into real numbers which incorporates risk attitudes and given preferences. Decisions made based on values $V(x)$ encode the strength of preference over wealth involving riskless attitudes, while utility encodes both the preference and risk attitudes (Krzysztofowicz 1983). Concerning uncertainty, von Neumann and Morgenstern assumed that all probabilities should be decided objectively. It was later expanded by Savage (Savage 1954) who introduced subjective probabilities into the expected utility maximization models, which contributed greatly to modern decision analysis.

The utility function and the value function can be mapped as:

$$U(x_i) = W(V(x_i)) \tag{5.1}$$

The expected utility equation assumed the linear relationship between the probabilities and the utility (Weijs 2011) . Expected utility can be written as:

$$E(U\{x,p\}) = \sum_{i=1}^{n} U(x_i) p_i \tag{5.2}$$

Where $W(\cdot)$ is the individual's utility function, $V(x_i)$ is the consequence of the attributes, e.g. monetary outcomes, in the *i*-th state of the future world, and p_i is the probability of the ith state of the world. $E(U\{x,p\})$ is the expected utility. According to the utility theory developed by von

Neumann and Morgenstern, X is preferred to Y if and only if the expected utility of X is larger than Y.

$$X \succ Y \ \ iff \ E\big(U(X)\big) > E(U(Y)) \tag{5.3}$$

5.3 Existing methods for decision making under uncertainty

5.3.1 Classic decision making

Classic decision making specifies the likelihood of future uncertain states using probabilistic information, estimates the outcomes of decision alternatives, determines the decision makers' utility functions and helps decision makers to find the optimal decision in the sense that it has the highest expected utility. The crucial component required by classic decision making is to determine the probability distribution for future states of the world. Statistical methods can be used to determine the probability distributions on the basis of adequate historical data with the assumption of *stationarity*, which assumes the variables or events do not change in temporal and spatial scale. However, subjective probabilities are also suitable to estimate the future states of variables in case of uncertainty (Dessai and Hulme 2004). Subjective probabilities can be assigned using Bayesian models and expert judgement. Whether the uncertainty is well characterized and the decision model is well structured is important for finding the stochastically optimal decision (Morgan, Dowlatabadi et al. 2009).

The mathematical expression of classic decision making is as follows (e.g. discrete states): Let D denote the space of the viable decisions d_y to the problem; X denotes the space of scenarios to represent possible states x_z ; Θ denotes the space of possible outcome θ_{yz} given the decision d_y under the future state x_z. $p(\theta_{yz}|x_z, d_y)$ denotes the probability of the outcome given the specified state and the decision, $p(x_z)$ denotes the probability distribution of the future states; $u(\ \theta_{yz})$ is the utility given the outcome. The expected utility for each decision is expressed as:

$$E\big(U(d_y)\big) = \sum_{z \to Z} u(\theta_{yz}) p(\theta_{yz}|x_z, d_y) p(x_z) \tag{5.4}$$

The decision which has the maximal expected utility is the optimal decision according to the traditional expected utility maximization rule.

$$E(U(d_i^*)) \geq E\left(U\big(d_j\big)\right) \quad j \neq i \tag{5.5}$$

States →	x_1	$\cdots$	x_z	$\cdots$	x_Z	$EU(d)\ \downarrow$
Probabilities →	$p(x_1)$	$\cdots$	$p(x_z)$	$\cdots$	$p(x_Z)$	
d_1	$u(\theta_{11})$	$\cdots$	$u(\theta_{1z})$	$\cdots$	$u(\theta_{1Z})$	$\sum_{z\to Z} u(\theta_{1z})p(\theta_{1z}\|x_z,d_1)p(x_z)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$⋰$	$\vdots$	$\vdots$
d_y	$u(\theta_{y1})$	$\cdots$	$u(\theta_{yz})$	$\cdots$	$u(\theta_{yZ})$	$\sum_{z\to Z} u(\theta_{yz})p(\theta_{yz}\|x_z,d_y)p(x_z)$
$\vdots$	$\vdots$	$⋰$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
d_Y	$u(\theta_{Y1})$	$\cdots$	$u(\theta_{Yz})$	$\cdots$	$u(\theta_{YZ})$	$\sum_{z\to Z} u(\theta_{Yz})p(\theta_{Yz}\|x_z,d_Y)p(x_z)$
Decisions ↑						

Table 5.1 matrix of expected utilities functions under each decision. The top row defines each state of the world under uncertainty. Second row indicate the objective or subjective assessment of each state's probability of occurring. The first column lists the decisions under consideration. The interior of the matrix reflects the utility of the outcomes corresponding to each decision acting in each state. The rightmost column represents the expected utility of each decision *d* (Groves 2006).

Classic decision analysis has been widely applied in a range of water management problems in face of uncertainty. Examples includes flood management strategies (de Kort and Booij 2007), water quality management (Duchness, Beck et al. 2001), urban water supply system management (Kodikara 2008) and water infrastructure management (Chowdhury and Rahman 2008). The method allows defining multiple, and often conflicting objectives, quantifies uncertainty with probabilities explicitly, provides the consequences of each strategies against the objectives clearly, and enables decision makers to choose the optimal option straightforwardly. It can also be integrated with other decision making methods, such as scenario planning to analyse the strategies against different scenarios, real options to look at a strategy's uncertainty based on a comparison between costs and risk profiles, which are closely dependent on strategies (Means III, Laugier et al. 2010). However, classic decision analysis is suitable when uncertainty can be well characterized with probabilities, which is difficult to be implemented when uncertainty is complex and high-dimensional. Additionally, it provides one optimal option, which might not be resilient or adaptive to the uncertain future conditions.

5.3.2 Traditional scenario planning

Traditional scenario planning identifies a strategy that best and commonly prepares for a plausible set of uncertain circumstances (Means III, Laugier et al. 2010). Scenarios are developed through the identification of crucial uncertainties and driving forces, aiming to go beyond extrapolation of current trends and explore plausible future alternatives. Strategies are identified for each scenario, and then a near-term common strategy is selected to cope with all scenarios. In long-term planning, the strategy will be reassessed and adapted when a *signpost* occurs. *Signposts* are established to monitor the divergence of a scenario from the others or its original path, and determine when the strategies are no longer suitable to all or most scenarios.

Scenarios are descriptions of future state of the world in a consistent and plausible way, and they can be qualitative and quantitative. The development of scenarios is the crucial process to manage uncertainty for decision making purpose. Key uncertainties are identified and ranked based on the *importance level* and the *uncertainty level* with respect to the central questions (Means III, Laugier et al. 2010). The development techniques of scenarios for water resources planning and management have been reviewed by Dong et al. (2013). Traditional scenario planning treats scenarios equally likely to occur, instead of assigning probabilities to future states, as in classic decision analysis.

Scenario-based framework has been applied in water resources management under uncertainty, such as water policy development (Stewart and Scott 1995), water resources planning and watershed management (Mahmoud 2008, Mahmoud, Gupta et al. 2011), ecological protection (Zacharias, Dimitriou et al. 2005). Scenarios are useful when historical data or statistical information is not sufficient or necessarily required. It can be used in both short-term and long-term decision making, allowing decision makers to analyze the performance of strategies against different future conditions. However, typically future conditions are characterized by a small number of scenarios, which limits the ability of scenario planning to address uncertainty completely. Scenarios with diverse views might require disparate strategies and the method doesn't bring consensus of these strategies. Additionally, as probabilities are not available, it leads to arbitrary selection of scenarios and strategies.

5.3.3 Robust decision making framework

A robust strategy is defined here as one that performs well compared with decision alternatives over a large ensemble of alternative futures (Lempert, Groves et al. 2006). Unlike the optimal strategy focusing on the most likely futures, robustness takes into account less likely and extreme events or states of the future. The robust decision making method generates robust strategies adapted to large sets of quantitative scenarios through an iterative process. The process includes: (1) suggest initial candidate robust strategies, (2) identify vulnerability of the strategies against certain clusters of future circumstances, (3) suggest hedges that address vulnerabilities of the initial strategies, (4) characterize tradeoffs between the full range of futures and a cluster of future circumstances where strategies might perform poorly (Lempert, Groves et al. 2006). The robust decision making concept has been applied in water resources management under uncertainty. Groves (Groves 2006) has examined robust strategies for California water management strategies in the face of climate and socio-economic uncertainties, and Dessai and Hulme (Dessai and Hulme 2007) have identified adaptation strategies robust to climate change uncertainties for water resources management in the United Kingdom.

Robust decision making differs from the classic decision making approach without considering probabilities, which is consistent with the traditional scenario planning idea. However, it differs from traditional scenario planning by generating a large ensemble of scenarios using model simulations instead of narratives. The advantage of the method is that (1) a complete set of strategies is not required at the beginning of decision analysis, as adaptive strategies can be proposed in the process iteratively; (2) the consequence and vulnerability of each strategy to future conditions is identified, and it enables decision makers to determine their own objectives and risk acceptance in long-term plans. However, sophisticated computation and analytic abilities is required in the process. Generally, robust decision making does not determine one single best strategy. Instead, it uses the information in computer simulations to distinguish the reasonable choices from the unreasonable ones, and to demonstrate the tradeoffs among the reasonable options. Robust decision making requires high level of decision-maker engagement (Groves, Knopman et al. 2008), as they have to assign their own subjective likelihood to the critical scenarios, estimate their acceptance level of the strategies' vulnerabilities, and select one final robust strategy.

5.4 Decision making rules for water resources management under uncertainty

Decision rules are used to rank candidate decision alternatives under uncertainty and find out the optimal and robust decision given the outcomes of decision alternatives against future conditions. Xu and Tung (2009) have reviewed and summarized four categories of decision rules in water resources planning and management. Among them, three popular categories will be introduced. In addition, decision rules based on utility theory can be used when decision makers' preference and attitudes to wealth and risk are taken into account.

5.4.1 Classic decision rules

Various classic approaches exist: mean-value method, Markowitz mean-variance method, minimax regret or maxmin value method (Markowitz 1959, Duchness, Beck et al. 2001, Xu and Booij 2004, Figueira, Greco et al. 2005, de Kort and Booij 2007). The mean-value method compares different alternatives on the basis of the expected value of consequences; the Markowitz mean-variance method selects the alternative with smaller variance for the same expected value, or the larger expected value for identical variance; the maxmin rule tries to find the alternative which minimizes the maximal loss value based on a simple pessimistic view, and the minimax rule chooses the preferred alternative by minimizing their maximum regret (opportunity loss if the alternative is chosen instead of others). These methods are easy to implement. However, they will miss information provided by probability distributions generated by model outcomes, as they only focus on the first or second moments or the single best or worst outcome. As shown in Figure 5.1, the decision makers might have difficulty in choosing a better decision merely based on the mean value (Left figure) and mean-variance rule (Right figure) if they don't take into account the entire probability distribution (Tung, Wang et al. 1993).

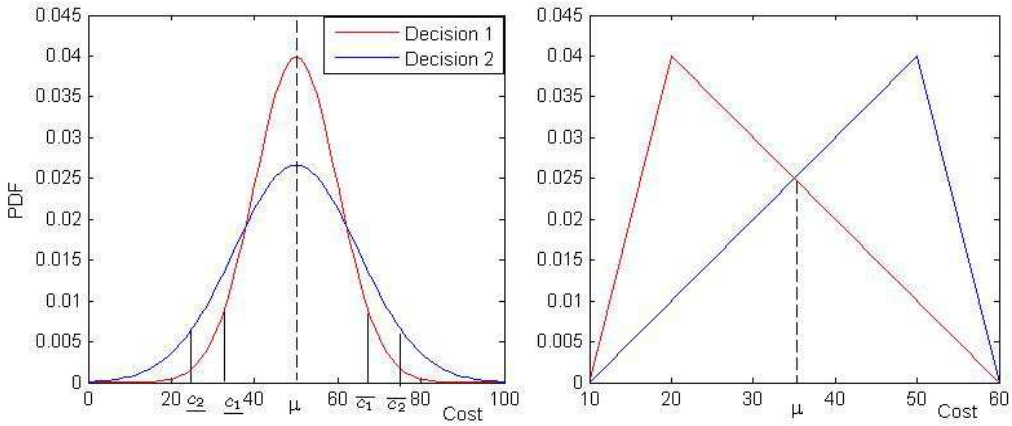


Figure 5.1 Consequences of two alternatives with same mean (left) and same mean and variance (right).

5.4.2 Statistical decision rules

A widely used stochastic decision rule is the stochastic dominance (*SD*) rule (e.g.,Tung, Wang et al. 1993, Tung and Yang 1994). Stochastic dominance has been applied in decision theory since (Allais 1953). The *SD* rule focuses on the ordering of uncertain options for specific risk profiles (Levy 1992). For example, *SD* rules were applied to compare candidate alternatives by comparing the risk profile, which represents the cumulative probability distribution (CDF) of consequences from decision alternatives. Three degree levels, namely, first-degree stochastic dominance tests (*FSD*), second-degree stochastic dominance test (*SSD*) and third-degree stochastic dominance test (*TSD*) were developed gradually due to the complexity of dominance characteristics between CDFs. Mathematically, these can be expressed as follows,

$$\delta F_{1-2}^{(1)}(x) = \int_{-\infty}^{x} [f_1(y) - f_2(y)]dy = F_1(x) - F_2(x) \geq 0 \text{ for all X; (FSD)}$$
$$\delta F_{1-2}^{(2)}(x) = \int_{-\infty}^{x} [F_1(y) - F_2(y)]dy = \int_{-\infty}^{x} \delta F_{1-2}^{(1)}(y)\, dy \geq 0 \text{ for all X; (SSD)} \quad (5.6)$$
$$\delta F_{1-2}^{(3)}(x) = \int_{-\infty}^{x} \int_{-\infty}^{v} [F_1(y) - F_2(y)]dvdy = \int_{-\infty}^{v} \delta F_{1-2}^{(2)}(y)\, dv \geq 0 \text{ for all } X;\ E_1(X) \leq E_2(X); \text{(TSD)}$$

Where $f_1(y)$ and $f_2(y)$ are the CDF of decision alternative 1 and 2, respectively. $E_1(X)$ and $E_2(X)$ are their expected value.

When the CDFs (cumulative density functions) of two decisions do not cross, the dominance relationship can be determined by the first-order stochastic domain (*FSD*) test. The *FSD* test determines that decision 1 dominates decision 2 iif (if and only if) $F_1(x) \geq F_2(x)$ for the case where *X* represents a "cost" (the less the better). Conversely, the dominance relationship between them is opposite when *X* represents a benefit (the more the better). Non-dominance between two alternatives requires a higher level stochastic dominance test. For example, the right figure shows that decision 1 dominates decision 2 by *SSD* as the area A is bigger than area B (Figure 5.2). However, higher degree of stochastic dominance requires extra assumptions, for example, the *SSD* test assumes the decision makers are risk averse and prefer a less risky outcome; the *TSD* test further assumes that the decision makers have a diminishing risk adverse attitude against the outcomes. The disadvantage of higher degree of stochastic dominance test are: (1) parametric probability distributions have to be assigned to the CDF for easier integral computation; (2) computation is more expensive when more integrals of the CDF are involved; (3) the assumed risk attitudes of decision makers are difficult to be justified in practice.

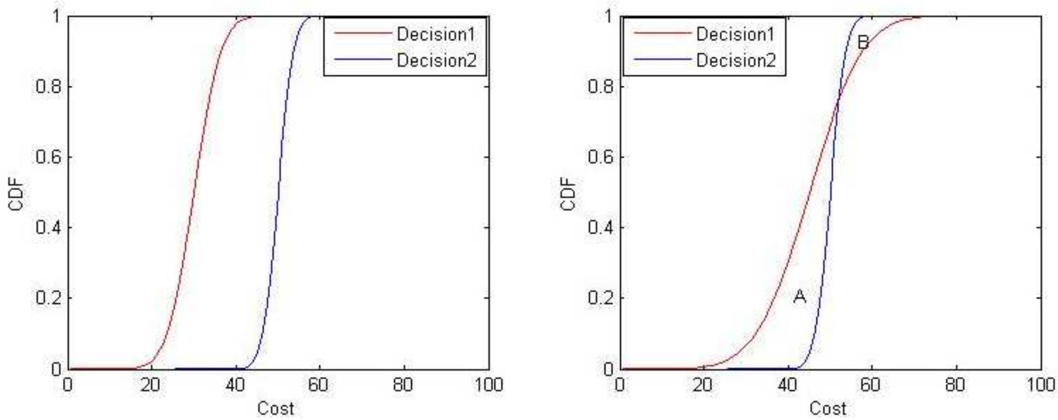


Figure 5.2 Decision 1 dominates decision 2 by *FSD* (Left) and *SSD* (Right).

5.4.3 Stochastic-Ranking-Based decision rules

Given that different possible rankings can be sampled statistically due to uncertainty, these rules measure the similarity or difference between pairs of ranking. Two measures, a rank correlation coefficient (Kendall 1948) and Xu's risk measure (Xu. Y. P. and Tung 2008) were developed for this purpose. The rank correlation coefficient is calculated over a score matrix which measures the agreement between pairs of ranking, and one alternative is ranked before others when the overall rank correlation coefficient between it and the others is larger than 1. Xu's risk measure presents the risk of obtaining a pair of weak ranking of alternatives and the corresponding expected loss. The risk was defined as the product between the probability of obtaining unacceptable ranking and the opportunity loss of the ranking. Decision makers have to decide whether they are willing to accept the risk or not.

5.4.4 Stochastic-Utility-Based decision rules

To combine the full probability information and the risky context, stochastic utility based rules follow expected utility theory and involve the context of decision makers' risk attitudes to uncertainty. The approach analyzes the risk profile associated with the utilities considering decision makers' risk attitudes (Schultz, Mitchell et al. 2010). This method ranks decision alternatives by maximizing the expected utility at a certain level of risk attitude of decision makers, and it can also analyze the sensitivity of the ranking by altering the risk attitudes.

Three risk attitudes of decision makers can be represented by different utility functions. They are risk neutral, risk averse and risk seeking (Figure 5.3). Risk neutral attitudes are described by a linear utility function, and decision makers evaluate the risk depending only on the values (model outputs), which linearly translate to utilities. Risk averse behavior is described by a concave utility function with decreasing marginal utilities. Decision makers are cautious and conservative when they deal with uncertainty. Conversely, risk seeking behavior has a convex utility function with increasing marginal utilities. For risk averse decision makers, the utility increases with increasing preference (returns, profits), and the marginal utility is decreasing.

$$U'(x) > 0;\ U''(x) < 0; \tag{5.7}$$

With risk seeking decision makers, the utility increases with wealth but the marginal utility is increasing:

$$U'(x) > 0;\ U''(x) > 0; \tag{5.8}$$

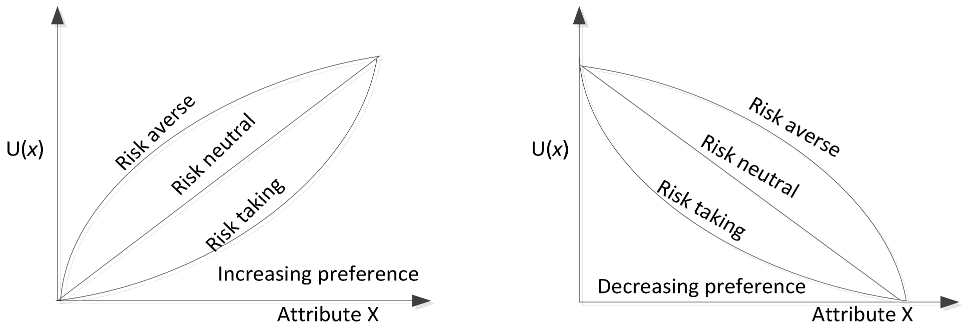


Figure 5.3 Utility function curves associated with different risk attitudes (Pinto and Garvey 2012).

Certainty equivalent (x_{ce}) is an important index to distinguish the risk attitudes of decision makers, and compare alternatives under the same risk attitude. It is the certain amount that is equally preferred to the expected value $E(X)$ of the alternative. For example, you can either play a game with 50% of $3000 gain and 50% of getting nothing, or you can have $1000 for sure. The expected value of playing the game is 0.5*$3000+0.5*0=$1500. If you prefer to accept $1000 for sure instead of playing the game, your certainty equivalent is $1000. In other words, you are conservative and resist taking the risk even with a higher expected return. Concerning risk averse against loss, for instance, you have to choose either losing $3000 with a probability of 50% and nothing with 50%, or lose $1700 for sure. The expected loss of the first choice is 0.5*$3000+0.5*0=$1500. If you choose to pay $1700 for sure instead of playing the gamble, then your certainty equivalent is $1700. In that case, you are risk averse and resist taking the risk even with a lower loss. In general, the behavior of taking a sure thing over a risky alternative which has higher expected return or lower expected loss is called risk averse; conversely, rejection of a sure thing under the same circumstances is called risk seeking.

The difference between the expected value and the certainty equivalent is called risk premium $R = E(X) - x_{ce}$. It is the minimal amount that the decision maker is willing to pay to compensate the risk to choose an uncertain alternative, or to avoid the risk to choose an uncertain alternative. On the other hand, from the uncertainty management point of view, the risk premium is the difference between the expected values of an alternative with and without considering uncertainty (Schultz, Mitchell et al. 2010).

Using certainty equivalent x_{ce}, the three different risk attitudes in terms of profits/returns can be specified as follows:

- $x_{ce} < E(X)$ or $R > 0$, If the certainty equivalent specified by the decision maker is less than the expected profit for a decision, the decision makers have a risk adverse attitude with respect to uncertainty.
- $x_{ce} = E(X)$ or $R = 0$, If the certainty equivalent specified by the decision maker is equal to the expected profit for a decision, the decision makers have a risk neutral attitude.
- $x_{ce} > E(X)$ or $R < 0$, If the certainty equivalent specified by the decision maker is greater to the expected profit for a decision, the decision makers have a risk seeking attitude.

However, these definitions have to be adjusted for outcomes specified in terms of decreasing preference such as costs. In that case, decision makers are risk averse if their certainty equivalent is greater than the expected cost, and risk seeking if their certainty equivalent is smaller than the expected cost.

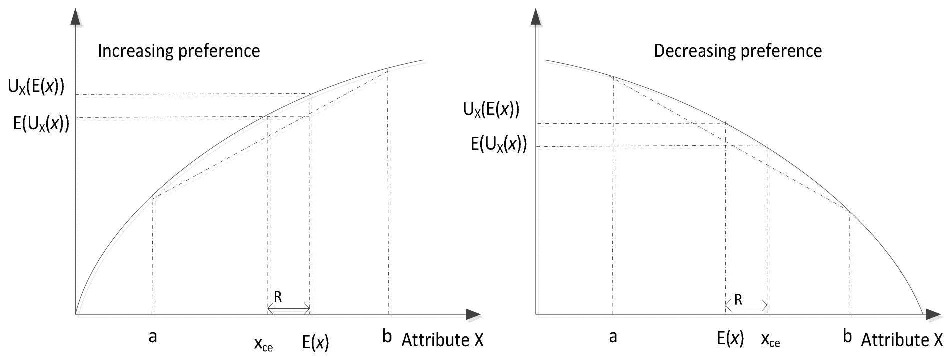


Figure 5.4 Certainly equivalent and risk averse attitude.

Mathematically, the utility corresponding to the certainly equivalent $\mathrm{x_{ce}}$ equals the expected utility of the decision alternative along the attribute X (Norstad 2011). Then,

$$\mathrm{U(x_{ce})} = E(U_X(x)) \tag{5.9}$$

$$\mathrm{x}_{ce} = U_X^{-1}(E(U_X(x))) \tag{5.10}$$

Therefore, certainty equivalent can be used as an index to compare the preference of decision makers on alternatives. To compare alternatives, the alternative with larger certainty equivalent is preferred in terms of profits as the expected utility is also larger, and with smaller certainty equivalent is preferred in terms of cost, providing that the appropriate utility function is used. In Figure 5.5, when decision makers' preference increases as the attribute increases, alternative 1 is preferred to alternative 2 as the certainty equivalent of alternative 1 is larger than that of alternative 2 , $\mathrm{x}_{ce1} > \mathrm{x}_{ce2}$, and $E_1(U_X) > E_2(U_X)$. Conversely, alternative 2 is preferred to alternative 1 as the certainty equivalent of alternative 1 is larger than that of alternative 2 ,

$x_{ce1} > x_{ce2}$, and $E_1(U_X) < E_2(U_X)$,when concerning the decreasing preference of decision makers.

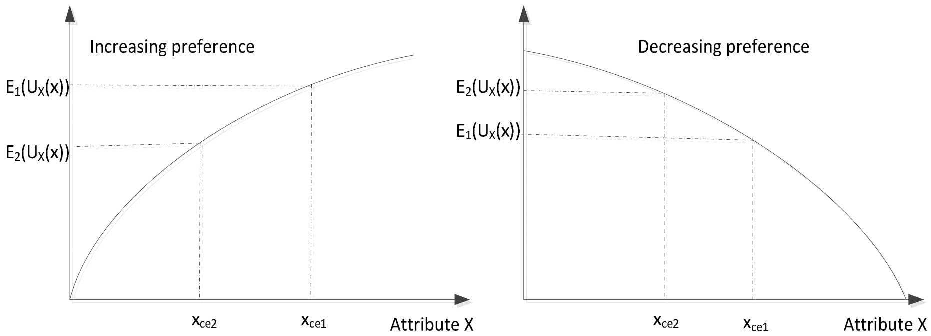


Figure 5.5 Certainty equivalent and alternatives ranking.

5.4.5 Comparison of different rules

Unlike classic decision rules, the other three methods take the full probability distribution into account. The full probability distribution is regarded to represent uncertainty better than several statistics and it provides more information. It is more likely to cover extreme cases, which is crucial to avoid large damage or loss.

Risk is interchangeable with uncertainty. Risk defined by engineers is the product of the damage due to hazards events and the probability of the events occurrence. Risk can be also defined from the decision makers' perspective, which is quantified by the amount of money that decision makers are willing to pay to assume or compensate the risk (Levy 1992). Among these methods, Only Xu's risk measure and utility-based decision rule take into account the decision makers' attitude and tolerance level towards risk when they have to make decisions under uncertainty. However, Xu's risk measure leaves the quantification and analysis of decision maker's preference to risks implicit, and the consequences of different risk attitude levels of decision makers are ambiguous to them. However, the advantage of the utility-based decision rule is that decision makers are asked to identify their preference and informed about the consequences explicitly if they overestimate or underestimate the risks.

As evaluated by Xu and Tung (2009), the decision rules have different computational requirements and ease of use. Classic decision rules have high computational efficiency and the results are easy to be used by decision makers. Statistical decision rules need to compare the full probability distributions using high degree dominance tests if necessary, which leads to high computational requirements. The results are easy to be implemented as the deterministic ranking is provided. Stochastic-Ranking-Based rules need relatively low computational capacity as a pair of alternatives is compared at a time, but the computational time will increase exponentially with the increasing number of alternatives. The results don't point out the deterministic ranking, and the decision makers have to choose a reasonable ranking according to the provided information. Stochastic-Utility-Based decision rules require relatively high computational capacity considering the computation of value functions as well as utility functions. The results are deterministic for an individual decision maker who is supposed to know his preference on wealth and risk beforehand. When a group of decision makers are involved, a consensus of utility functions is difficult to reach and various utility structures are required to resolve the issue. Therefore, the results can be non-deterministic for multi-decision makers.

Table 5.2 Comparison of different decision rules

Decision rules	Classic decision rules	Statistical decision rules	Stochastic-Ranking-Based	Stochastic-Utility-Based
Methods	mean-value method, Markowitz mean-variance method, min/max method	stochastic dominance	rank correlation coefficient and Xu's risk measure	Expected utility maximization and Certainty equivalence
Information needed	first and second moments of probability distribution	full probability distribution	full probability distribution, decision makers' opinions on uncertainty	full probability distribution, decision makers' opinions and risk attitudes on uncertainty
Risk informed	not informed	implicitly informs risk of each alternative against uncertainty	Xu's risk measure explicitly informs the risk of obtaining weak ranking	explicitly informs risk of each alternative against uncertainty and decision makers' risk attitude
Computing requirements	Low	Relatively High	Relatively Low	Relatively High
Ranking result	deterministic ranking	deterministic ranking	non-deterministic ranking	deterministic ranking

5.5 Probabilistic scenario-based decision making framework

5.5.1 Characteristics of the framework

A probabilistic scenario-based decision making framework incorporating uncertainty is proposed based on existing frameworks and decision rules. The framework tries to incorporate the strengths and compensate for the shortcomings of existing methods. The framework implements uncertainty management by developing scenarios, while modifying the traditional scenario development by generating a large number of quantitative scenarios using model simulations and Monte Carlo techniques, and explicitly addressing uncertainty with probabilistic information using Bayesian analysis and expert judgement, as demonstrated in Chapter 3 and 4. By doing so, problems can be avoided such as limited scenarios to display potential future circumstances, or arbitrary selection of scenarios and strategies due to lack of probabilistic information. The proposed framework takes the complete view of future states into account. It constructs probability distributions to assign continuous values to the variables, in order to test the decision alternatives against any value with a probability included in the scenarios. This allows the selection of robust decisions against the plausible range of future conditions. The process is designed to be adaptive, and signposts should be detected as new evidence and information becomes available. Additionally, the decision maker's uncertainty and risk tolerance level are quantified in the decision making framework, in order to explicitly provide multiple view to uncertainty and risk to decision makers (Keeney and Wood 1977). The comparison of existing frameworks and the proposed framework is listed in table 5.3.

Table 5.3 Comparison of different decision frameworks

Decision making methods	**Classic decision analysis**	**Traditional scenario planning**	**Robust Decision making**	**Probabilistic scenario-based decision making**
Uncertainty management	Probabilities are assigned to uncertain future states explicitly	Scenarios are developed to identify crucial uncertainties and driving forces of future states	Scenarios are generated by model simulations to represent uncertainty	Scenarios are generated to quantify crucial uncertainties by model simulations and Monte Carlo simulations
Probability information	Required	Not required	Not required	Required
Scenario number	Most likely scenarios	Few numbers	A large ensemble	A large ensemble
Output	Expected outcomes and expected utility of alternatives , and their rank	The performance of common strategy to cope with all scenarios, signposts are established for suggesting adaptive strategy	The consequences and vulnerabilities of strategies against scenarios	Risk profile of outcomes and utilities of strategies against scenarios and the associated probabilities and risks
Decision makers' involvement	In early stage and making final decision	The whole process of decision making	Highly engaged in the whole process of decision making	The whole process of decision making plus risk management
Decision makers' risk attitude	Risk neutral	Not specified	Not specified	Risk neutral, risk seeking ,risk averse
Decision selection	Deterministic	Not deterministic	Not deterministic	Deterministic
Decision type	Optimal against most likely scenarios	Robust and adaptive against developed scenarios	Robust and adaptive against a large ensemble of scenarios	Robust and rational against a large ensemble of scenarios

5.5.2 General procedure and approach

The general procedure and approach of the proposed framework are shown in Figure 5.6. The details are introduced below:

(1) Frame the decision problem. Identify the objectives / criteria and uncertain factors of the decision making problem. The objectives/criteria represent the preference and consideration of decision makers. They can be related to various dimensions, such as economic, environmental, political, and social aspects. In water resources planning and management, economic criteria are quite desirable and feasible such as maximize the net benefit of water projects, minimize the cost of infrastructures investment, etc. Objectives/criteria are mathematically expressed by the objective functions. The objective functions are usually expressed in monetary terms, such as loss function or payoff function. They quantify the cost or benefit across any possible state when any of the decisions would be put into practice.

(2) Propose the decision candidates which are viable. A pool of decision alternatives should be proposed and identified for further consideration and selection based on the objectives/criteria. The decision candidates can be generated through brainstorming to ensure a set of creative and viable decisions are included (Xu, Booij et al. 2007).

(3) Manage uncertainties in the decision problem. Identify critical uncertainties and driving forces, and assign probabilities to related variables to address uncertainty. Build and validate water management models to propagate uncertainty of driving forces using hydrologic models, water demand models, or water quality models to simulate future states of water availability, water demand or water quality. Scenario analysis, Bayesian probability and Monte Carlo analysis have been widely applied in uncertainty analysis and strategic decision making in environmental studies (Varis 1997, Middelkoop, Kwadijk et al. 2002, de Kort and Booij 2007). In this framework, scenario development associated with Bayesian Monte Carlo analysis is selected as the approach to explore future states and their probabilities.

(4) Compute the criteria performance against scenarios. Cost-benefit analysis, or cost-effectiveness analysis when the benefit is difficult to estimate, is most popular for rational decision making. Economic criteria such as expected cost, cost-benefit ratio, or net benefit are widely used to evaluate the performance of each decision alternative. The probabilistic scenarios of water variables serve as input to the objective function, and the risk profile representing the values of each decision alternative can be constructed using the outcomes of Monte Carlo simulation. In addition, utility functions are constructed to assess and analyse the influence of decision maker's risk tolerance levels on the final choice of decision.

(5) Rank and evaluate alternatives. Alternatives are ranked and evaluated based on the full risk profile of outcomes and utilities, and stochastic dominance is suitable for that purpose. The alternative with higher expected utility is more desirable and receives higher rank. The ranking results can be sensitive to the use of various decision models, ranking methods, different criteria or preference from multiple decision makers. Sensitivity analysis is necessary to test the robustness of the ranking strategies and decision making. It shows the decision maker which parameters or assumptions have large impact on the model outcomes and ranking strategies of alternative decisions (Schultz, Mitchell et al. 2010). To analyze the sensitivity of rank results on the risk tolerance from different decision makers, certainty equivalent can be a useful index to compare the performance of each alternative.

In the decision making process, decision makers are highly involved. Their opinions on uncertainty and risk, and their expectations on the alternative performances determine the selection and acceptance of the final decision. If the decisions ranked and selected in the formal round is not accepted by decision makers, the decision making process can be repeated with a new set of decision alternatives.

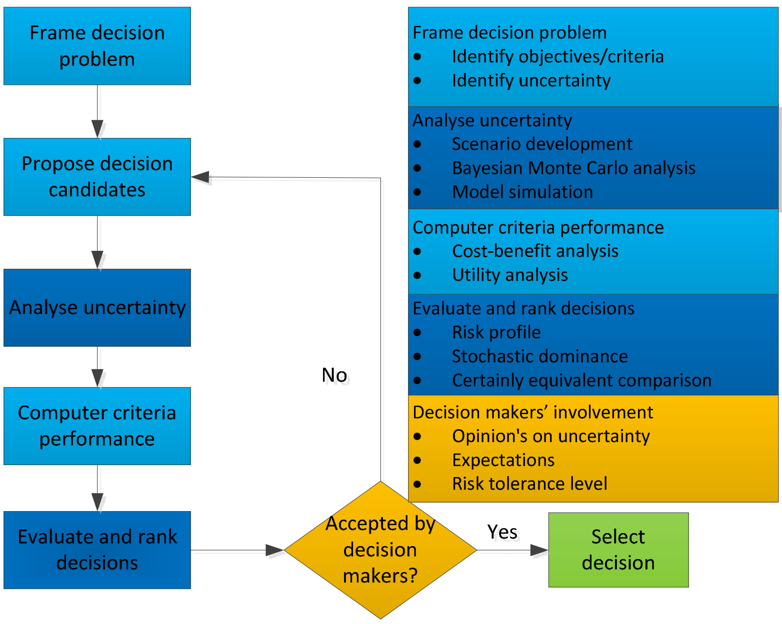


Figure 5.6 The proposed framework for decision making under uncertainty.

5.6 Conclusion

This chapter reviewed and compared existing decision frameworks and the decision rules for decision making incorporating uncertainty in the field of water resources planning and management. Indeed, uncertainty management decides the quality of decisions that will be made, and existing frameworks have their own strong and weak points when dealing with uncertainty. A probabilistic scenario-based decision making framework is proposed based on existing frameworks. It is different from any single framework, by introducing a large set of scenarios to explore a plausible range of future alternatives, and probabilistic information to explicitly quantify uncertainty. On the other hand, the choice of an appropriate decision rule is also crucial for ranking alternatives and incorporating the decision maker's preference. The framework includes the use of utility functions to take into account the preference of decision makers towards both wealth and risk. Besides the maximal expected utility rule, a risk index, certainty equivalent is used to represent the difference between expected utilities of decision alternatives with and without considering uncertainty. In summary, the proposed decision making framework hopes to help decision makers to make robust, adaptive decisions rationally under uncertainty, and at the same time, to understand the influence of decision makers' opinions and risk attitudes under uncertainty on the decision making results. An application of the proposed framework is discussed in Chapter 6.

Chapter 6 Probabilistic scenario-based decision making under uncertainty in the Yellow River Delta (YRD), China

6.1 Introduction

The Yellow River Delta, an important area for food production as well as a base of petroleum production, comprises an area of about 6000 km^3 and feeds a population of 1.8 million. Economically, the YRD has received great attention from the government since one of the priority projects "Development and conservation in the Yellow River Delta" listed in China's Agenda 21 (ChinaGovernment 1994). Ecologically, the Yellow River Delta Nature Reserve, a State Nature Reserve, contains the largest newborn wetland in China and abundant aquatic biological resources (Li, Yuan et al. 1999). With the prediction of increasing water demand for population growth, food and petroleum production, industrialization and sustainable ecosystem, reliable and sufficient water supply becomes a challenge for the next decades, in order to empower the development of the YRD.

YRD is short of local water resources and heavily depends on the Yellow River. With limited and polluted surface water and saline groundwater in the YRD, approximately 90% of the water resources are provided by the Yellow River (Li, Fan et al. 2011). However, the annual discharge from the Yellow River to the YRD has decreased greatly in the past decade due to the significant decline of annual water availability in the YR and an increase in upstream water diversions. Between 1970s and 1990s, zero-flow occurred frequently in the downstream YR. Especially in 1997, no water was available in the YRD for 226 days, which had an extremely negative impact on the socio-economic activities as well as the ecological sustainability in the YRD (Yang, Li et al. 2004). To strategically mitigate the effect of water shortages, the State Council approved the '*1987 Water Allocation scheme*'. The YRD is allowed to obtain maximally 0.728 km^3 of water from the YR, although the actual water allocation averaged 0.916 km^3 from 2002 to 2010 (Li, Fan et al. 2011). Due to the complex and uncertain changes in water availability in the YR and upstream water diversions, it is not clear whether current allocations can be maintained.

In previous chapters, probabilistic scenarios of future water availability in the YR (Chapter 3) and water demand in the YRD (Chapter 4) have been developed that account for potential changes in climate, socio-economic and environmental factors. This chapter aims to match the future water supply and demand given the developed scenarios. To fill the gap between the future water supply and demand in the YRD, two types of measures are recommended according to (Groves 2006, Li, Fan et al. 2011): (1) increase water supply by developing new supply sources, for example, by measures such as inter-basin water transfer, wastewater treatment, rain harvesting, or desalination. (2) Improve water use efficiency to decrease water demand while maintain economic development. Water use efficiency in the YRD is much lower than developed countries, for instance, 40% ~ 50% for irrigation water use and 63% water reuse for industrial, compared with 70% ~ 80% and more than 90% respectively in developed countries (Li, Fan et al. 2011). There is large potential for improving water use efficiency and saving substantial water resources. Water managers have to figure out what combinations of management strategies are cost-effective for meeting future water demand in the YRD when both water supply and water demand are uncertain. For this purpose, the proposed probabilistic scenario-based decision making procedure will be implemented to identify robust and cost-effective management measures to fulfill the water shortage.

6.2 Decision making framework

The proposed decision making framework is used to support the decision making considering the uncertain future water supply and demand conditions in the long-term water resources planning in the YRD. New water supply and more efficient water use are two efficient solutions for the future water shortage problem in China (2030WaterResourcesGroup 2009), but costs needed to implement these measures determine their effectiveness and desirableness. Table 6.1 shows the component of the decision making framework, including the external parameters required for the models, management measures, decision models and analysis used in the decision making process. Three critical models used in the decision making framework are as follows: (1) scenario development for future water supply and water demand in a probabilistic manner to cope with uncertainty; (2) cost-effectiveness analysis used to investigate the performance of each water management measure considering the cost over the water supply and demand scenarios; (3) expected utility analysis incorporating the decision makers' preference and risk attitudes to the management measures besides the monetary comparison, and demonstrating the impact of the decision makers' different risk attitudes on the decision making result.

Table 6.1 Decision making framework components

Parameters	***Management measures***
- Future water demand - Future water supply - Unit cost of new supply - Unit cost of efficiency improvement - Unit cost of supplementary supply - Discounting rate (3%) - Risk tolerance level of decision makers	***Water supply increase*** - New water supply project (0,1,2) - Supplementary supply (wastewater treatment) ***Water demand decrease*** - Water use efficiency improvement by 5%, 10%, 15%, 20% and 25%
Costs	***Models and analysis***
-Water use efficiency improvement -New supply projects investment -Supplementary supply investment	Water supply scenarios development (2010-2039) Water demand scenarios development (2010-2039) Cost- effectiveness analysis Expected utility analysis

In this chapter, the main steps of the probabilistic scenario-based decision making are the following:

1) Decision framing: this step is to understand the decision problem, identify the decision objective or criteria, and propose decision alternatives (equal as water management measures).

2) Uncertainty analysis: this step is to generate large ensemble of scenarios to represent uncertainty in the decision problem in a probabilistic way.

3) Evaluate and rank decision alternatives: this step is to generate and compare the risk profiles of both the monetary and utility-based outcomes of decision alternatives in order to choose the optimal and desirable decision. The information provided by the full probability distributions of outcomes is used and stochastic decision rules are implemented to rank decisions.

4) Sensitivity analysis: this step is to test the robustness of the chosen decision for different values and probability distributions of the parameters in decision making models, as well as for different decision making environment such as a group of decision makers with different preference and risk attitudes.

The decision process and the result have to be communicated and discussed with decision makers, in order to involve the opinions and preferences of the decision makers and increase the understanding between scientists and the decision makers. For example, the uncertainty analysis should involve the opinions and knowledge from the decision makers; the utility function should be formatted according to the decision maker’s preference; and the choice of the final decision should be checked if it is acceptable and adoptable. The probabilistic scenario-based decision making framework is flexible and repeatable as it allows for updating the probabilities if more knowledge becomes available and the adaption of management measures if the future deviates from the pre-defined scenarios.

6.3 Formulation of the decision problem

6.3.1 Objective functions

The decision problem is to match the future water supply and water demand in the YRD for the next 30 years, given the uncertain future water supply, water demand and policy situations. The objectives are both monetary-expressed and utility-based. The monetary objective is to minimize the total cost for preventing future water shortages. Mathematically, the objective function is written as:

$$Min_i\ (PC|D_i, X) = \sum_T \frac{(C_t|D_i, X)}{(1+d)^t} \tag{6.1}$$

where PC is the present cost of the decision alternatives, D_i is the ith decision alternatives, X are random variables representing uncertainty considered in the decision model (e.g., water supply, water demand and unit price of decision alternatives) , C_t is the cost of implementing the decision alternative in the t^{th} year, d is the discount rate, T is the total planning horizon (in this case, from 2013 to 2039), and the cost of alternatives must be estimated each year, discounted and aggregated over the planning horizon.

To take into account risk attitudes towards uncertainty, a utility-based objective is also considered, which aims to maximize the expected utility against the monetary outcomes of the decision alternatives under uncertain situations. The objective function can be written as:

$$Max_i\ (E(U(PC|D_i, X))) = E(U(\sum_T \frac{(C_t|D_i, X)}{(1+d)^t})) \tag{6.2}$$

Where U is the utility function associated with the cost function, and $E(U)$ is the expected utility.

6.3.2 Decision alternatives

Decision candidates focus on increasing water supply and decreasing water demand separately or combined. The strategy is to start from consider expanding water supply by adding new water projects, and then reducing water demand by improving efficiency. New supply to the YRD comes mainly from the Yangzi River through the South-to-north water transfer project, which is estimated to provide an additional water supply of approximately 2×10^8 m^3 per year from 2015 onward (Li, Fan et al. 2011). Water supply generated by investment of water treatment plants can be a supplement when water from the new supply project still cannot meet water demand. Decision makers would face the problem of how to choose the new supply strategies. If the water supply strategy cannot provide enough water for the future, it will influence the living standard and production in the YRD; however, if the water supply strategy provides more water than is required, it would cause the waste of water resources as well as money. To decide if an additional water supply project is required, '*signpost*' policies are considered to trigger new supply projects adaptively to provide more water supply but with slightly higher unit cost in future conditions. Water supply can be added through the investment of up to 2 water supply projects (NS = 0, 1, 2). If the signpost policy contains NS=0, the first signpost is triggered in 2015. If the future water supply and demand in the next 10 years shows one new water supply project is needed, then one project will be built in 2015 and NS=0 converts to NS=1. If the future water supply and demand in the next 10 years after 2015 shows another water project , the second new water project will be triggered and built in 2025, and NS=1 converts to NS=2. On the other hand, the water use efficiency improvement includes water use for both agriculture and industry, by 5%, 10%, 15%, 20% and 25%. It starts to be invested and implemented from 2013 onward. These management measures can be implemented separately, named d1 to d7, as shown in table 6.2. New water project (NS=0, 1, 2) and water use efficiency improvement by certain percentage is combined, named d8 to d17. Likewise, the water shortage after any management measures is fulfilled by higher-cost supplementary supply.

Table 6.2 Proposed water management measures

Decision alternatives	**Explanation**	**Capacity**	**Start year**
d1	1 water supply project	0.1km3	2015
d2	1 more water supply project plus d1	0.1km3	2025
d3	Agriculture and industry water use efficiency improvement	5%	2013
d4		10%	2013
d5		15%	2013
d6		20%	2013
d7		25%	2013
d8	Combination of d1 and d3		
d9	Combination of d1 and d4		
d10	Combination of d1 and d5		
d11	Combination of d1 and d6		
d12	Combination of d1 and d7		
d13	Combination of d2 and d3		
d14	Combination of d2 and d4		
d15	Combination of d2 and d5		
d16	Combination of d2 and d6		
d17	Combination of d2 and d7		

6.4 Scenario analysis of water supply and demand in the YRD

6.4.1 Water supply in the YRD

Water supply in the YRD (WS_{YRD}) comprises of discharge form the YR (WS_{YR}), and local surface water WL_{YRD} and groundwater WG_{YRD}. According to the data between 1987 and 2010, the water supply from the YR contributed 83% of the total water supply (Figure 6.1). Due to the water pollution in the local rivers and the brackish groundwater, the local water contributed much less. The total water supply is written as:

$$WS_{YRD} = WS_{YR} + WL_{YRD} + WG_{YRD} \tag{6.3}$$

As water supply in the YRD heavily depends on the YR, the focus is on the future water availability situations in the YR (WA_{YR}) . Considering the uncertainty of water availability and the water division in the YRB, water availability of the YR for the YRD (WA_{YRD}) is crucial to decide the water supply in the YRD. On the other hand, water supply from the local water resources is planned to be 2.84×10^{8} m^{3} from the surface water and 1.15×10^{8} m^{3} from the groundwater, according to the water resources planning in (Li, Fan et al. 2011).

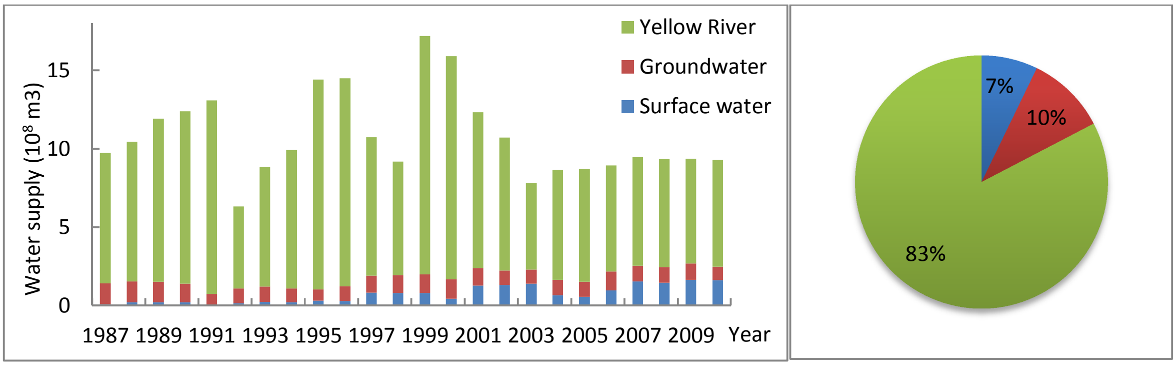


Figure 6.1 Water supplies from three sources in the YRD between 1987 and 2010.

Two steps have to be implemented to find out the future water availability from the YR to the YRD, WA_{YRD}:

(1) Predict future runoff of the YR considering climate change impact, WA_{YR} ;

(2) Obtain the water availability from the YR to the YRD by deducting water withdrawal by nine provinces in the YRB as well as two regions outside the basin, WL_{YRB}, and the environmental water requirement WD_{env}.

$$WA_{YRD} = WA_{YR} + WG_{YR} - WL_{YRB} - WD_{env} \tag{6.4}$$

Where WA_{YRD} is water availability from the YR to the YRD; WA_{YR} is the future runoff in the YR; WG_{YR} is the available groundwater capacity, $WG_{YR} = 11km^3$; WL_{YRB} is the water allocated and consumed in the YRB; WD_{env} is the environment water requirement, the optimal value is 21 km^3 to keep in-stream healthy ecological system and sedimentation transportation; and the minimal value is $5km^3$ to guarantee the environmental water requirement for base flow in non-flooding season (Li 2008). To maintain the ecosystem in the YRD Nature Reserve, the minimal environment water requirement is 0.686 km^3. In the analysis, the minimal environmental water requirement is always first satisfied before the YRD withdrawals water from the YR.

6.4.1.1 Future runoff in the YRB, WA_{YR}

Considering the climate change impact on the runoff in the YRB, a conceptual rainfall-runoff model was used to simulate and predict future runoff. Probabilistic scenarios of climate variables were constructed and used as input of the model to compute runoff. The procedure has been explained in chapter 3. The results of the rainfall - runoff models are different when considering different uncertainty sources such as the input, model parameters, residual errors, and overall uncertainty. The average historical runoff between 1960 and 1990 is 82.57mm, and the average future runoff between 2010 and 2039 is 76.66mm, 75.16mm, 75.13mm and 76mm respectively. The average annual runoff decreases by 7.15%, 8.97%, 9.01% and 7.95%. As the mean value is insufficient to represent all the information contained in the simulated runoff, four parametric probability distributions are assigned, which are lognormal distribution, normal distribution, gamma distribution and weibull distribution. Figure 6.2 shows the probability distributions fit of the simulated future runoff, and the historical annual runoff between 1960 and 1990. The index (*1, 2, 3, 4*) in figure 2 shows the simulated runoff considering the four types of uncertainty sources, respectively. The four probability distributions fit the simulated data well except that the weibull distribution over-fit the low runoff. In figure 6.2(4), lognormal distribution overestimates both the low and high runoffs. Overall speaking, normal distribution and gamma distribution fit the model simulation data better than the other two probability distributions. To compare the impact of uncertainty from each source on the simulated runoff, the uncertainty from the input is larger than the uncertainty from the model parameters, as the probability density function (PDF) are much narrower than when input uncertainty is considered. The PDF of the runoff considering the input uncertainty has a slightly fatter tail on the high runoff, compared with the PDF considering uncertainty from the model parameters and residual errors. Considering the sufficient uncertainty from both the input and the hydrological model, to analyse the overall uncertainty

(Figure 6.2(4)) is useful to increase the confidence of the decision making, although the accumulation of uncertainty makes the decision making more complex. In the following analysis to estimate the future water availability in the YRD from the YR, the simulated runoff considering the input uncertainty (Figure 6.2(1)) and the overall uncertainty (Figure 6.2(4)) will be applied to distinguish the climate change impact from the hydrological model.

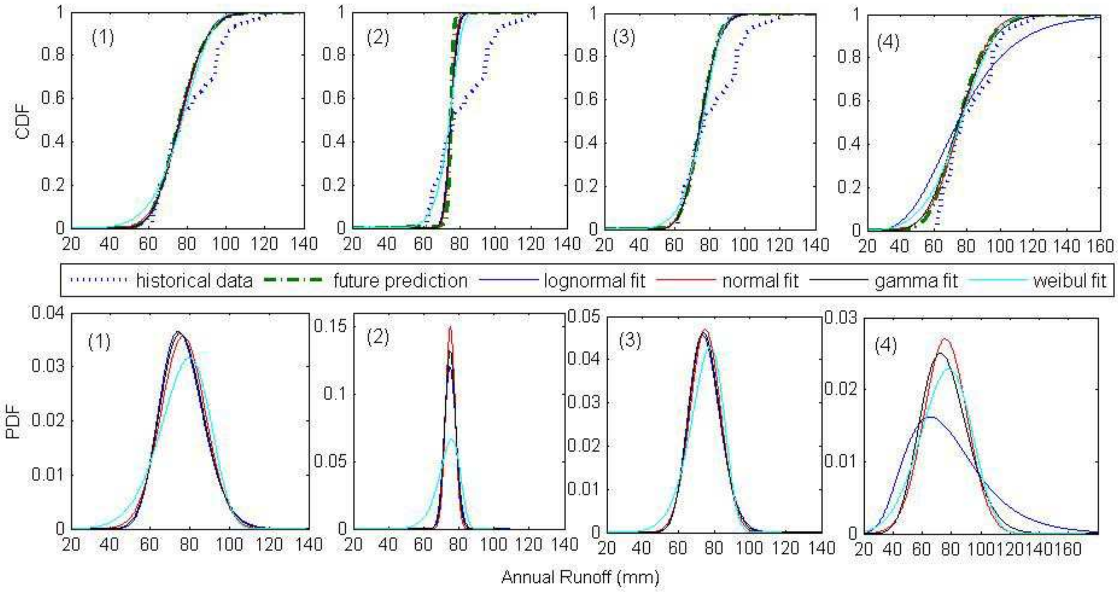


Figure 6.2 CDF of historical runoff (1960-1990) and future runoff (2010-2039) when considering different uncertainty sources, (1) uncertainty only from input; (2) uncertainty only from model parameters; (3) uncertainty from model parameters and errors; (4) uncertainty from all parts. Four parametric probability distributions fit of future runoff.

6.4.1.2 Future water withdrawal in the YRB, WL_{YRB}

The water withdrawal is decided by the water demand as well as the water allocation scheme in the YRB. At present, the water demand in these areas reaches 73.04km^3. YRCC projects that water demand will reach 59km^3 by 2030 and 64km^3 by 2050 besides 21km^3 environmental/ecological water requirements, and the water shortage is estimated to be 11km^3 and 16km^3 if no measures would be taken (Li 2008). To settle down the big conflict between water demand – supply and prevent zero-flow at the downstream, the *Yellow River 1987 Water Allocation scheme* was formulated by the National Council based on the report by the National Plan Commission and the Water Conservation Department. The total water allocation is 37 km^3/year in the YRB (0.78km^3/year in the YRD). The number was calculated by deducting 21km^3 for in-stream eco-environment water requirement from the 58km^3 average annual runoff from 1919 to 1975. The '*1987 Water Allocation scheme'* was revised in 1998 considering the decline of water availability in the YR, and the water allocated to the YRD became 0.728km^3 (Yang, Shao et al. 2010). The implementation of the 1987 water allocation scheme brings the gain of environmental sustainability at the expense of economic loss. Li (Li 2008) calculated the economic cost by 2030. The irrigation output will reduce by 233.5 billion RMB, the industrial output will drop by 17.5 billion RMB, the crop yield will decrease by 29730 ton/year and the GDP will decline by 627.9 billion RMB. Regions downstream of the YR, including the YRD, would encounter even larger economic loss. The future water withdrawal of the YRB is crucial to maintain the production and development of the YRB, as well as the water availability in the YRD and the eco-environment requirement.

Two scenarios *S1* and *S2* are developed to explore the future water allocation in the YRB by emphasising two extreme aspects: the environmental sustainability and socio-economic development:

S1:'1987 Yellow River Water Allocation Scheme', the water abstraction insists the allocation quota WA_{1987} *(36.272km^3) to prevent zero flow even though it may cause slow socio-economic development in the 30 years.*

S2:'Demand-based Allocation scheme', the water allocation WL_{YRB} *satisfies the water demand in the Yellow River Basin* (WD_{YRB}) *to maximize socio-economic development while guaranteeing the minimal environment water demand.*

To quantify the future water allocated in the YRB (WL_{YRB}) , scenarios *S1* and *S2* can be seen as the minimal and maximal extremes of the water allocation schemes. The possible futures between the extremes are also taken into account by assigning a uniform distribution in the range (uniform distribution is the maximal entropy distribution given two values of the intervals).

$$p(WL_{YRB}) = \begin{cases} \frac{1}{WD_{YRB} - WA_{1987}}, & WA_{1987} < WL_{YRB} < WD_{YRB} \\ 0, & WL_{YRB} < WA_{1987} \ \ or \ \ WL_{YRB} > WD_{YRB} \end{cases} \tag{6.5}$$

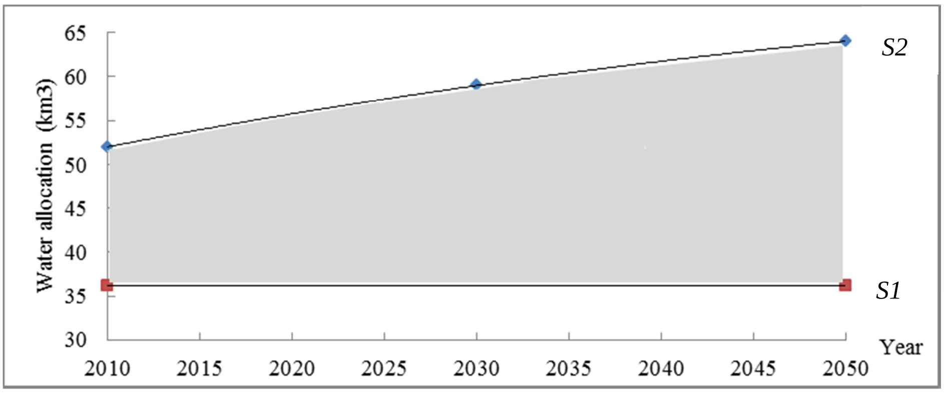


Figure 6.3 Scenarios of annual water allocation in the YRB.

6.4.1.3 Future water availability from the YR to the YRD, WA_{YRD}

Eight cases associated with the future water withdrawal scenarios in the YRB are taken into account to analyse the water availability in the YRD from the YR. A Monte Carlo technique was applied to sample from the distributions of the future water availability and water withdrawal. The eight cases are as follows: (1) *The Four parametric probability distributions* of the future runoff simulated considering only the input uncertainty *(LN1, N1, G1, W1)*; (2) *The Four parametric probability distributions* of the future runoff simulated considering the overall uncertainties *(LN4, N4, G4, W4)*.

Figure 6.4 shows the 99% uncertainty band and the median value of water availability into the YRD. The annual water availability is decreasing, and it is consistent with the historical trend. When considering overall uncertainty sources, the uncertainty band of water availability is wider than that when considering only input uncertainty by approximately 10 km^3. As the lognormal distributed runoff has a long tail when considering overall uncertainties, it also contains much higher upper bound than that of the other distributions. Zero water availability occurs as a result of low water availability and high water demand scenarios in the YRB. Table 6.3 lists the values of the 99% uncertainty band of the water availability in the YRD. The 0.5 percentile of water availability corresponds to the worst case, which is zero flow in all situations. The medium water availability is between 15 km^3 to 17 km^3 in 2010, and it drops largely to 11 km^3 and 12 km^3 in 2039. The upper bound drops mostly by 1 km^3. But the Lognormal and Weibull distributions lead to the increased values, due to their overestimation of the high runoff in the YRB (Figure 6.2(4)).

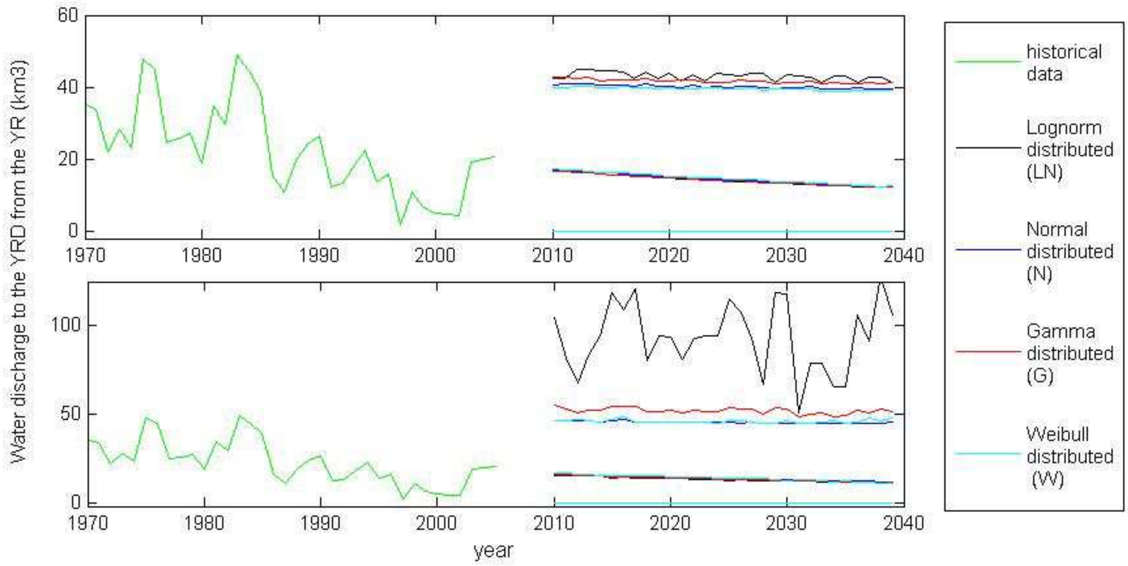


Figure 6.4 0.5%, 50% and 99.5% percentile (lower, middle and upper lines, respectively) of annual water availability in the YRD from the YR when the runoff is lognormal, normal, gamma and weibull distributed. The green line is the historical water discharge. The top figure shows the uncertainty band when considering input uncertainty due to climate change, and the bottom one shows that when considering all uncertainties. The lines are not continuous due to the lack of data.

Table 6.3 0.5%, 50% and 99.5% percentile of water availability in the YRD from the YR at the year 2010 and 2039

Percentile	0.5%		50%		99.5%	
Year	2010	2039	2010	2039	2010	2039
LN1	0	0	16.65	12.23	42.84	41.17
N1	0	0	16.95	12.32	40.66	39.69
G1	0	0	16.65	12.27	42.51	41.47
W1	0	0	17.23	12.56	39.90	39.09
LN4	0	0	15.21	11.16	104.99	106.13
N4	0	0	16.45	11.82	46.71	45.28
G4	0	0	15.81	11.41	55.01	51.84
W4	0	0	16.7	11.02	46.70	47.73

Note: *LN, N, G, W* represents lognormal, normal gamma and weibull distributed runoff in the YRB, (1) and (4) represents the runoff considering only climate change uncertainty and overall uncertainties.

According to the *1987 Water Allocation scheme (Li, Fan et al. 2011)* , Water supply in the YRD from the YR should be no more than 0.728 km^3. Therefore, three types of the future water supply are formed, which are zero supply when zero flow occurs in the downstream, the maximal supply when water availability is no less than 0.728 km^3, and non-zero supply between the zero and maximal supply. Figure 6.5 shows eight cases about future water supply in the YRD (*WS1*, *WS2*,

WS3, *WS4*, *WS5*, *WS6*, *WS7*, *WS8*) under the eight cases (*LN1*, *N1*, *G1*, *W1*, *LN4*, *N4*, *G4*, *W4*) and the probabilities of the three types of water supply. According to Table 6.4, the maximal supply has the largest chance to occur in the future, and the zero supply occurs less when only input uncertainty is considered. The supply between the two types has small probability to occur in the future.

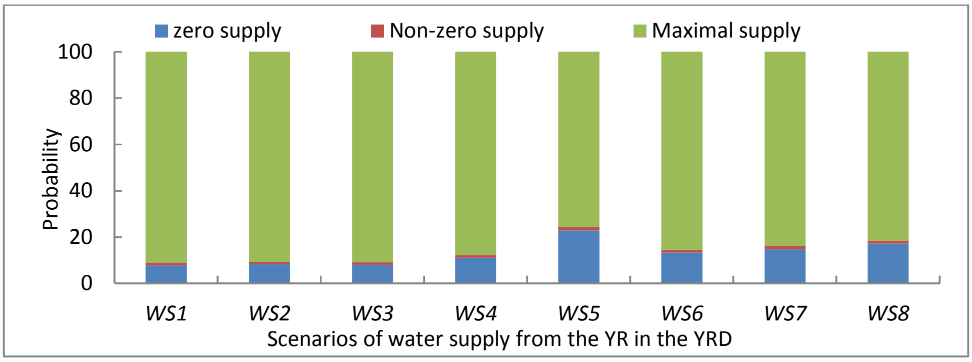


Figure 6.5 Probability of water supply scenarios from the YR to the YRD

Table 6.4 Probability of three types of water supply in the YRD from the YR (%)

	WS1	*WS2*	*WS3*	*WS4*	*WS5*	*WS6*	*WS7*	*WS8*
Zero-supply	7.73	8.22	7.89	11.05	22.76	13.26	14.73	17.08
Non-zero supply	1.18	1.13	1.16	1.13	1.38	1.27	1.39	1.25
Maximal supply	91.09	90.65	90.95	87.82	75.86	85.47	83.88	81.67

6.4.2 Water supply-demand analysis

Probabilistic scenarios of annual water demand in the YRD from 2010-2039 have been described in Chapter 5. The total water demand in the YRD has the tendency of increasing. Instead of considering the blue water footprints (consumptive use of ground- and surface water flows) (Hoekstra, Chapagain et al. 2011, Hoekstra, Mekonnen et al. 2012), the water demand scenarios are explored to analyze the future water conditions against water supply. Figure 6.6 shows the example of the distribution of annual water shortage under the cases *WS2* and *WS6* in the YRD between 2010 and 2039. To analyze the impact of future water demand on water shortage situations, the water demand with deterministic (annual average water demand) and stochastic (probability distribution of annual water demand) values are taken into account separately to calculate the water shortage. The distributions of annual water shortage are presented in the top and bottom figures, without and with considering water demand uncertainty, respectively. According to the figures, some findings can be addressed:

(1) There are two peaks of water shortage around -0.25km^3 /year and -1km^3 /year, which is consistent with the high probabilities of minimal and maximal water supply in cases *WS2* and *WS6*. The right peak is higher and wider than the left peak, as the maximal water supply is more likely to occur in both cases.
(2) Water shortage located in the left peak under case *WS2* is slightly less than that under scenario WS6, as the probability of minimal water supply occurs in *WS2* is lower than that in *WS6*.
(3) Without considering the uncertainty from the water demand in the YRD, the range of water shortage is smaller than that of taking into account the water demand uncertainty.

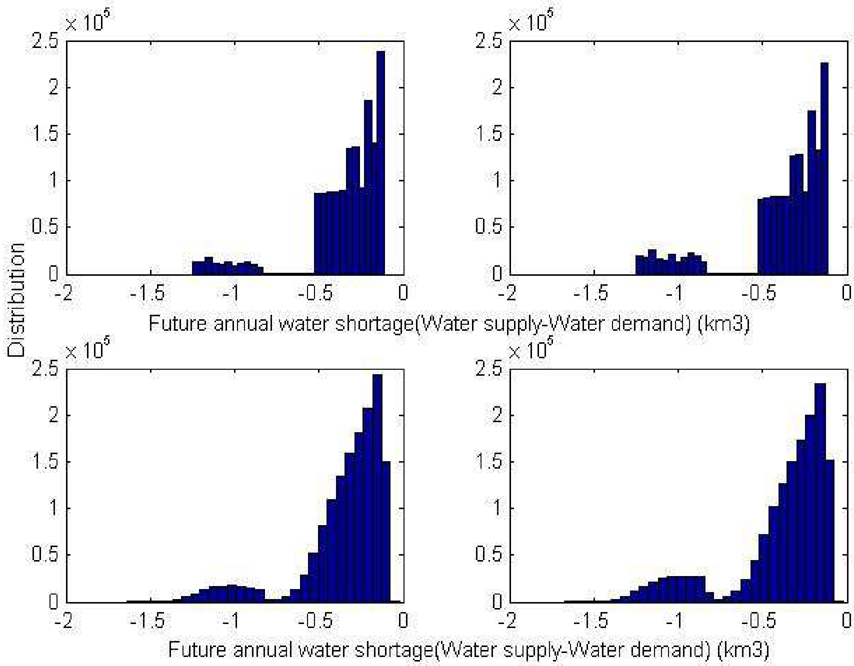


Figure 6.6 Distribution of annual water shortage (water supply-water demand) between 2010-2039 in the YRD, under the scenarios *WS2* (left) and *WS6* (right), associated with deterministic and probabilistic water demand the YRD, (top) and (bottom) respectively.

6.5 Performance of water management strategies

6.5.1 Cost analysis

The total cost includes the cost invested to build new water supply projects C_{np}; improve water use efficiency C_{Eff} ; and supplementary water supply by expanding wastewater treatment capacities C_{ss} if there is any shortage between water demand and additional water supply. Considering different water management strategy portfolios, the total cost of specific strategy under future states can be written as below:

$$(C_t|D_i, X) = (C_{Eff}|E, P_e, D_i, X) + (C_{np}|N_{np}, S_{np}, P_{ns}, D_i, X) + (C_{ss}|P_{\Delta Q}, \Delta Q, X) \tag{6.6}$$

Where E is the water use efficiency improvement strategy, P_e is the unit price of water saving from the efficiency improvement, N_{np} is capacity of new water supply projects, S_{np} is the signpost to trigger a new water supply project, P_{ns} is the unit cost of water from the new water supply project, and ΔQ is the water supply deficit after management measures are adopted. $P_{\Delta Q}$ is the unit price to fill the deficit.

New supply projects follow the basic features: (1) the project construction cost is amortized over the lifetime of the project; (2) the amortized cost must be paid even if the supply is not used (Groves 2006). The unit cost of the first new water supply project is specified to be 0.012\$/m^3. The second project triggered by the signpost policy cost 20% more than the former one, since the cost of labour, land or material is assumed to increase in the future.

The unit cost of reducing water demand by improving efficiency is assumed to increase as higher efficiency is reached. The unit cost of different efficiency improvement is simplified by the formula:

$$UC_{(effh)\%} = UC_{(effl)\%} * (1 + a) \tag{6.7}$$

Where $UC_{(effh)\%}$, $UC_{(effl)\%}$ are the unit cost of efficiency improvement by higher percentage and sequential lower percentage. a is the growth rate of additional cost. In the model, 5%, 10%, 15%, 20% and 25% efficiency improvement is assumed, and the additional cost is assumed to be 20% compared to the sequential lower percentage. The unit cost of improving irrigation and industry water demand by 5% is specified to be 0.02 \$/m^3 and 0.025\$/m^3.

The supplementary supply is required when water shortage still exists even with the additional water provided by new water projects, and the water demand reduction. The supplementary supply is from expanding wastewater treatment, and the unit cost is assumed to be higher than the other two decision candidates, which is 0.04\$/m^3.

6.5.2 Expected utility analysis

Utility can measure the strength of decision makers' preference and risk attitudes; however, there is no unique equation that objectively yields the strength. But an equation can be selected for comparative measure of the strength. The Iso-elastic utility and negative exponential utility functions are mostly used, and the explanation can be found in (Norstad 2011). Garvey (Garvey 2008) introduced a common and convenient form of exponential utility function, considering the decision makers' preference on both gains and losses. An implicit assumption in this form of the exponential utility function is that the decision maker expresses a constant risk attitude over all levels of wealth and risk, which contradicts the prospect theory proposed by Kahneman and Tversky (1979). The exponential utility function has been applied in decision making under uncertainty by (Schultz, Mitchell et al. 2010, Gonzalez, Payán et al. 2012).

If utilities are monotonically increasing over the levels X for an evaluation criterion 'more is preferred', such as profit, and then the exponential utility function can be written as:

$$U(x) = \begin{cases} \frac{1-e^{-(x-x_{min})r}}{1-e^{-(x_{max}-x_{min})r}}, & r \neq 0 \\ \frac{x-x_{min}}{x_{max}-x_{min}}, & r = 0 \end{cases} \tag{6.8}$$

If utilities are monotonically decreasing over the levels X as 'less is preferred', such as cost, and the exponential utility function is written as follows:

$$U(x) = \begin{cases} \frac{1-e^{-(x_{max}-x)r}}{1-e^{-(x_{max}-x_{min})r}}, & r \neq 0 \\ \frac{x_{max}-x}{x_{max}-x_{min}}, & r = 0 \end{cases} \tag{6.9}$$

Where r is the **risk tolerance** parameter. It determines the shape of the utility curve. If r is positive, the utility function is concave, representing risk averse attitude. If r is negative, the utility function is convex, representing risk taking attitude. If $r \to 0$, the utility function is risk neutral. The curves away from the risk neutral one describe higher levels of risk averse or risk taking behaviour. Figure 6.7 shows nine shapes of utility that reflect an individual's risk attitudes with increasing preference and decreasing preference. The curves approaching the risk neutral line represent less risk averse behaviour when $r > 0$ and less risk taking behaviour when $r < 0$.

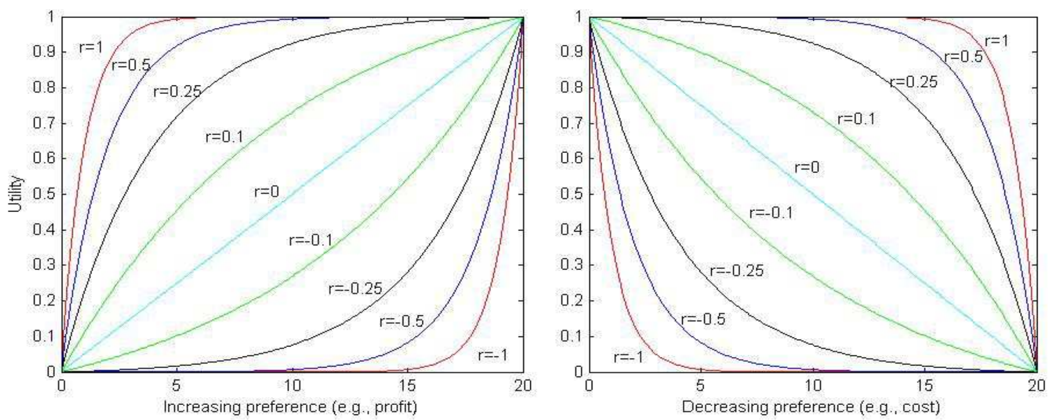


Figure 6.7 Utility of different risk-tolerance level with increasing preference and decreasing preference.

6.5.3 Compare and rank alternatives

In this section, the decision making procedure will be carried out by dealing with uncertainty in the following manner: water shortage scenarios are generated according to water supply scenario *WS2* associated with probabilistic water demand in the YRD, and the market price of water management measures are defined as the deterministic value described in 6.4.1. Sensitivity analysis will be implemented in order to test the robustness of the outcomes of decision analysis in the next session.

6.5.3.1 Decision making without considering utility explicitly

If the decision maker makes decisions only based on the monetary or physical term, the decision objective is to minimize the expected cost under uncertainty. Figure 6.8 shows the mean and standard deviation of the monetary outcomes from each alternative. The mean value and standard deviation represent the expected cost and the corresponding uncertainty (risk) of obtaining the mean value. According to the Markowitz mean-standard deviation decision rule (Markowitz 1959), a better decision alternative should have both smallest mean cost and standard deviation. However, this cannot lead to a specific ranking, as no alternative has the smallest mean value and standard deviation simultaneously.

Instead, a risk profile is used to represent the cumulative probability distribution over possible costs of a decision alternative against the probabilistic range of water supply and demand scenarios. Figure 6.9 shows the risk profiles of the 17 decision alternatives with the fixed parameters of the cost effectiveness model. The five most cost effectiveness decision alternatives (d2, d8, d9, d13, d14) were selected based on first-order statistic domain analysis, and the rest is abandoned in the following analysis. They are shown on the right of the figure.

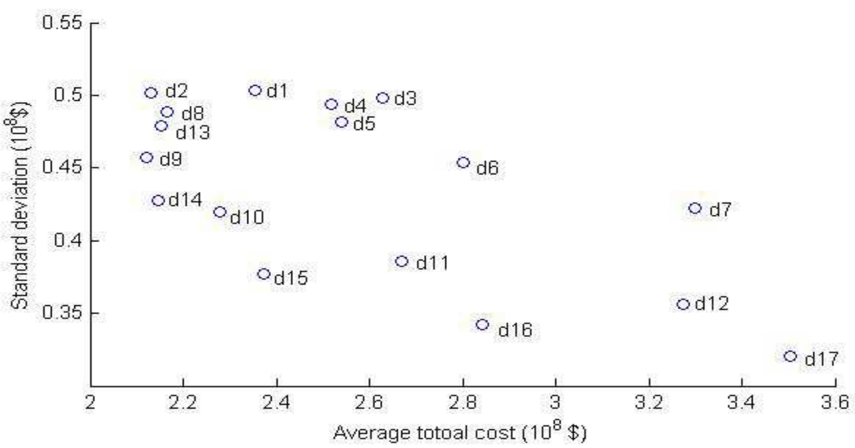


Figure 6.8 Mean and standard deviation of total cost from 17 decision alternatives.

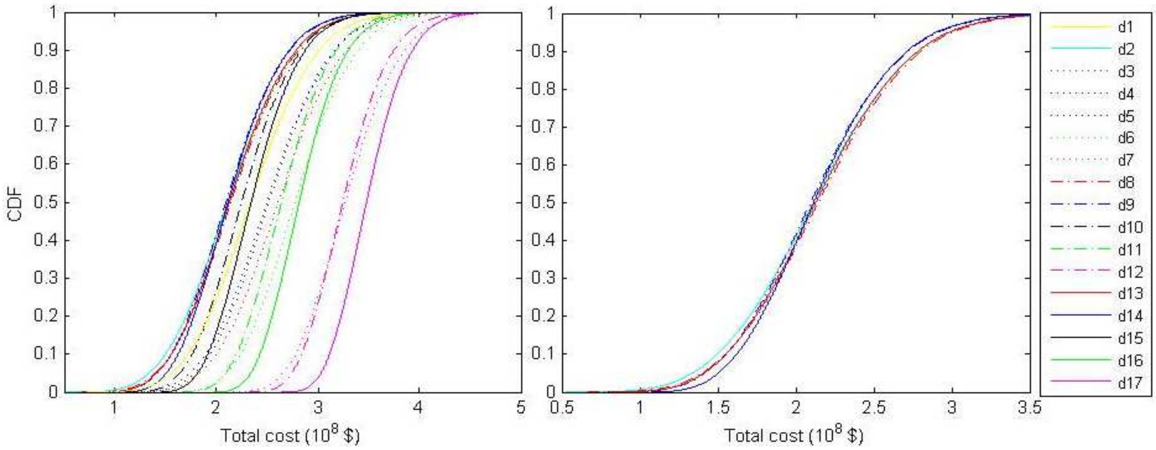


Figure 6.9 Risk profiles of the total cost from decision alternatives, left figure shows the risk profiles of 17 alternatives, right one shows the risk profiles of the 5 most cost-effectiveness alternatives.

The total cost of decision alternatives ranges approximately from 0.5×10^8 $ to 5.5×10^8 $. The range of the 5 selected alternatives is narrowed to 0.5×10^8 $ to 3.5×10^8 $. The risk profiles are crossed on the right figure. The *SSD* (second-order stochastic dominance) test is required to rank the decision alternatives, by assuming the decision makers are risk averse. Table 6.5 shows the results of the *SSD* test when fitting the CDF of the total cost by (a) normal distribution, (b) lognormal distribution, (c) gamma distribution, (d) weibull distribution, (e) best-fit distribution. *MSE* (Mean Square Error) was used to evaluate and measure the goodness-of-fit of the four parametric distributions to the total cost. For decision alternative d2, d8, d9, d13, d14, the best-fit distributions are normal, lognormal, gamma, normal and lognormal distribution, respectively. Under the five conditions, the rank of alternatives is as follows:

(a) Normal distributed: d2 < d8 < d13 < d9 < d14;
(b) Lognormal distributed: d2 < d8 < d13 < d9 < d14;
(c) Gamma distributed: d14 < d13 < d9 < d2 < d8;
(d) Weibull distributed: d14 < d9 < d2 < d13 < d8;
(e) Best-fit distributed: d8 < d2 < d14 < d13 < d9.

The ranking result is sensitive to the assignment of probability distributions to the outcomes of decision alternatives. The 'best' decision d14 (2 water supply projects plus 10% water use efficiency improvement) when the outcomes are normal or lognormal distributed becomes the 'worst' when they are gamma or weibull distributed. However, the most plausible ranking result ought to be consistent with that when the best-fit probability distribution is assigned, that is, d9 (1 water supply projects plus 10% water use efficiency improvement) is the best decision.

Table 6.5 *SSD* test matrix between alternatives

a	d2	d8	d9	d13	b	d2	d8	d9	d13	c	d2	d8	d9	d13
d2					d2					d2				
d8	N				d8	N				d8	N			
d9	N	N			d9	N	N			d9	P	P		
d13	N	N	P		d13	N	N	P		d13	P	P	P	
d14	N	N	N	N	d14	N	N	N	N	d14	P	P	P	P
d	d2	d8	d9	d13	e	d2	d8	d9	d13					
d2					d2									
d8	N				d8	P								
d9	P	P			d9	N	N							
d13	N	P	N		d13	N	N	P						
d14	P	P	P	P	d14	N	N	P	P					

Note: matrix *a*, *b*, *c*, *d*, *e* represent the *SSD* test results when the total cost is normal, lognormal , gamma, weibull , best-fit distributed respectively. N and P denote negative and positive value. Each element denotes the CDF of the column alternative minus that of the row alternative.

6.5.3.2 Decision making with considering utility explicitly

If the decision maker is willing to include the preference towards risk, the objective becomes to maximize the expected utility. Risk tolerance parameter can represent the comparative risk attitudes. Figure 6.10 shows the risk profiles of utility when the risk tolerance parameter equals to -2, 0, and 2, which quantify the risk taking, risk neutral and risk averse level of the decision maker. When $r = -2$, the values of utility are mainly distributed in [0,0.3]; when $r = 2$, the values of utility are mainly distributed in [0.8,1]. It can be explained as the risk taking person would prefer paying much less to achieve the same goal (for example, relieve water shortage) than the risk averse person, the utility to pay the same amount for the risk taking person is also lower than that of the risk averse person.

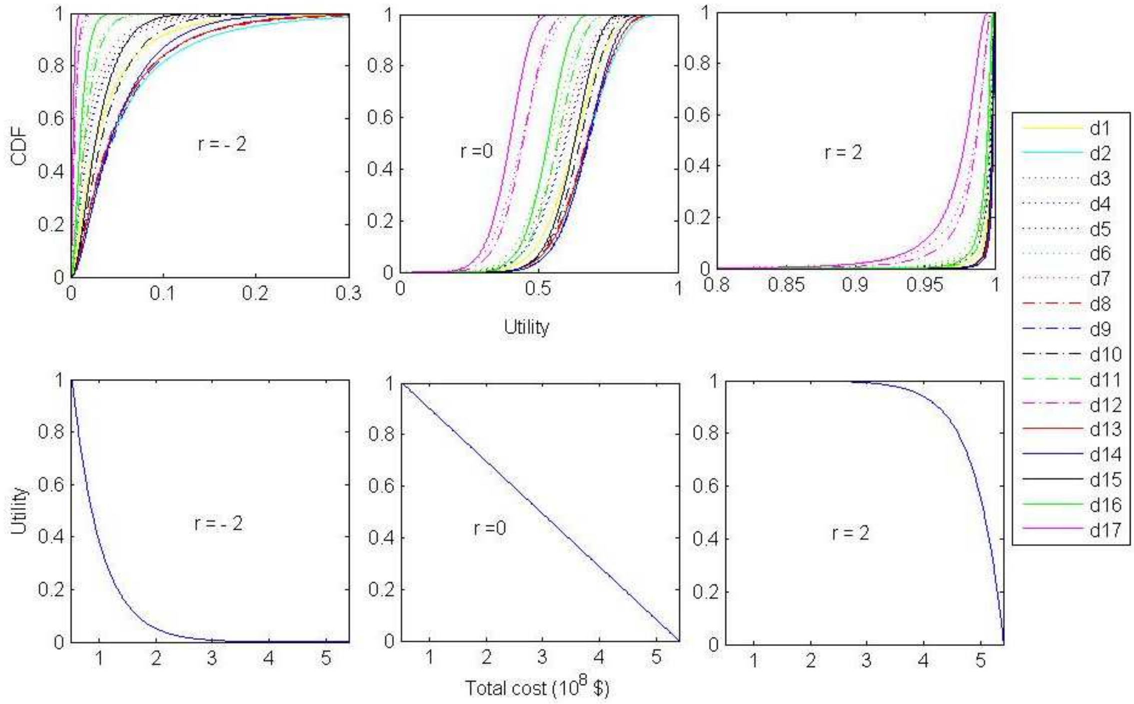


Figure 6.10 Risk profiles of utility from the decision alternatives under different risk tolerance levels (*r*= -2, 0, 2).

Table 6.6 Expected total present cost (*PC*), expected utility and certainty equivalent of 5 decision alternatives

Decision criteria	Risk tolerance parameter	Risk attitude	Unit	d2	d8	d9	d13	d14
$E(PC\|D_i,X)$			10^8 $	2.1315	2.1652	2.1217	2.1541	2.1472
$E(U(PC\|Di,X))$	-2	risk taking		0.0645	0.0586	0.0602	0.0584	0.0542
Xce			10^8 $	1.8994	1.9468	1.9338	1.9486	1.9862
$E(U(PC\|Di,X))$	0	risk neutral		0.6715	0.6646	0.6735	0.6669	0.6683
Xce			10^8 $	2.1315	2.1652	2.1217	2.1541	2.1472
$E(U(PC\|Di,X))$		risk averse		0.9976	0.9975	0.9978	0.9976	0.9978
Xce	2		10^8 $	2.4047	2.4265	2.3539	2.4083	2.3562

The 5 alternatives (d2, d8, d9, d13, d14) dominate the rest in terms of utility. Table 6.6 lists the expected total present cost, expected utility and certainty equivalent under three risk attitudes of the 5 decision alternatives. The goal is to pick the decision alternative with the maximal expected utility or the smallest certainty equivalent. The ranking result is different when the risk attitudes are different. A risk neutral and risk averse decision maker would choose d9 gives the highest expected utility and smallest certainty equivalent; while a risk taking decision maker would prefer d2 for the same reason.

6.6 Sensitivity analysis

Sensitivity analysis can test the robustness of the decision analysis results when altering the parameter values or probability distributions in the decision making model. It can also demonstrate the decision analysis carried out in different decision environments, such as individual decision maker or a group of decision makers. In this section, sensitivity analysis will be implemented to test the robustness of the decision analysis results both for the uncertainty in the decision models and the decision environments. The "one-at-once" rule will be applied in the sensitivity analysis, which means one parameter value will be changed and the other parameters are constant in every test. The sensitivity analysis for the decision model is carried out by altering the probability distributions of the future water supply in the YRD (*WS1 to WS8)* and the future water demand in the YRD (*deterministic water demand with considering the uncertainty (mean values) and probabilistic water demand with considering the uncertainty (probability distributions)*), and the market price of the water management measures. The "one-at-once" rule is applied by altering the probability distributions, while the values of other parameters such as market prices and risk tolerance parameters are assumed to be constant. The sensitivity analysis for different decision environment is implemented by changing the risk tolerance parameters. For a single decision maker, he is supposed to know his own value and preference, while the assignment of probability distributions and market price are uncertain to them. For multiple decision makers, besides the uncertainty faced by a single decision maker, the diversity of risk tolerance levels among them is a key parameter of interest. Altering the risk tolerance parameter is supposed to demonstrate the different interests and risk attitudes among decision makers, and to explain the difficulty to reach the consensus between different decision makers.

6.6.1 Sensitivity analysis for probability distribution patterns

Table 6.7 shows the sensitivity analysis results for different probability distributions of the future water supply and whether or not considering uncertainty in future water demand, when the decision maker has a risk taking, risk neutral and risk averse attitude. When the decision maker is risk taking (r = -2), the optimal decision is not sensitive to the assignment of probability distributions, but sensitive to the water demand situations. d9 (1 new water projects plus 10% water use efficiency improvement) and d2 (2 new water projects) are the optimal decision under each water demand situations. When the decision maker is risk neutral (r = 0), the optimal decision is not sensitive to either the probability distributions or the water demand situations. d9 performs better than other alternatives in the term of minimizing the total cost and maximizing the expected utility. When the decision maker is risk averse (r = 2), the lognormal distributed and the weibull distributed water supply scenario (*WS5* and *WS*8) provide different result from other probability distributions. The expected utility and certainty equivalent of d14 (2 new water projects plus 10% water use efficiency improvement) and d9 are similar, and d14 performs slightly better than d9. When analyzing the influence of different values of risk tolerance parameter (r= -2, 0, 2), the optimal decision remains the same when deterministic water demand is taken into account regardless of the different risk attitudes. Under the probabilistic water demand situation, risk taking decision makers prefer d2, while risk neutral and risk averse decision makers prefer d9. The decision result is least sensitive to the patterns of probability distributions of water supply compared with the other two factors.

Table 6.7 Sensitivity analysis for different probability distributions and risk attitudes

(a) Sensitivity analysis when the decision maker is risk taking, r = -2								
Water supply	*WS1*	*WS2*	*WS3*	*WS4*	*WS5*	*WS6*	*WS7*	*WS8*
Deterministic water demand	d9	d9	d9	d9	d9	d9	d9	d9
Probabilistic water demand	d2	d2	d2	d2	d2	d2	d2	d2

(b) Sensitivity analysis when the decision maker is risk neutral , r =0								
Water supply	*WS1*	*WS2*	*WS3*	*WS4*	*WS5*	*WS6*	*WS7*	*WS8*
Deterministic water demand	d9	d9	d9	d9	d9	d9	d9	d9
Probabilistic water demand	d9	d9	d9	d9	d9	d9	d9	d9

(c) Sensitivity analysis when the decision maker is risk averse, r = 2								
Water supply	*WS1*	*WS2*	*WS3*	*WS4*	*WS5*	*WS6*	*WS7*	*WS8*
Deterministic water demand	d9	d9	d9	d9	d14	d9	d9	d14
Probabilistic water demand	d9	d9	d9	d9	d14	d9	d9	d9

6.6.2 Sensitivity analysis for market price of management measures

Table 6.8 provides the sensitivity analysis result to the unit price of water management measures for risk taking, risk neutral and risk averse decision makers. The unit cost was treated as deterministic numbers in the decision model. However, it is necessary to analyze the influence of different market price on the selection of decision, as the price can change over time due to factors beyond the control of decision makers (Schultz, Mitchell et al. 2010). The change of unit price generates more diverse results, and the decision makers' risk attitudes have less influence on the decision compared with the market price. Five unit prices of new water projects lead to two optimal choices under each risk tolerance level. d13 (2 new water projects plus 5% water use efficiency improvement) is more preferred for a risk taking decision maker when the new water project has a lower unit price, while d14 becomes more preferable for risk neutral and risk averse decision makers. It makes sense as 2 new water projects are more economic efficient at low prices compared with efficiency improvement. However, higher unit price of new water project reduces the popularity of building new water projects, and d9 becomes more preferred. The change of the unit price of efficiency improvement can lead to a similar conclusion. With low unit price of efficiency improvement, the measure to improve water use efficiency by large percentage becomes more satisfactory so that d10 (1 new water projects plus 15% water use efficiency improvement) or d9 are preferred. When the unit price goes higher, d2 performs better. The fluctuation of the market price of supplementary supply leads to three different optimal choice under each risk attitude. When the unit price of supplementary supply is quite much lower than other measures, d1 (1 new water project and supplementary supply) becomes favorable; when the price goes up, d2 and d14/d15 are favorable. With the increment of the unit price, measures such as new water project or efficiency improvement become more cost effective.

Table 6.8 Sensitivity analysis of the market price of water management measures and different risk attitudes

Unit price of water projects ($/m3)	0.006	0.008	0.016	0.02	0.024
risk tolerance parameter *r*= -2	d13	d13	d9	d9	d9
risk tolerance parameter *r*= 0	d14	d14	d9	d9	d9
risk tolerance parameter *r*= 2	d14	d14	d9	d9	d9
Unit price of efficiency improvement ($/m3)	0.01	0.015	0.02	0.025	0.03
risk tolerance parameter *r*= -2	d10	d9	d2	d2	d2
risk tolerance parameter *r*= 0	d10	d9	d9	d2	d2
risk tolerance parameter *r*= 2	d10	d9	d9	d2	d2
Unit price of supplementary supply ($/m3)	0.005	0.025	0.065	0.085	0.1
risk tolerance parameter *r*= -2	d1	d2	d14	d14	d14
risk tolerance parameter *r*= 0	d1	d2	d14	d15	d15
risk tolerance parameter *r*= 2	d1	d2	d14	d15	d15

6.6.3 Sensitivity analysis for different risk tolerance parameter

Figure 6.11 shows the expected utility value and the certainty equivalent of decision makers with different risk attitudes under *WS2* and probabilistic water demand in the YRD. d2, d9 and d14 are favorable compared with others with higher expected utility and lower certainly equivalent against all risk tolerance levels. d2 performs better than the others when decision makers are risk taking. When decision makers are risk neutral, d9 is more preferred. As the decision maker becomes more risk averse, their preference shifted from d9 to d14 gradually. This can be explained with the information provided by the risk profiles of the total cost (Figure 6.12). The risk profile of d2 has higher probability in both lower and higher cost compared with d9 and d14.

A risk-taking decision maker is willing to take the risk with higher probability of higher cost, in order to have more chance to achieve much lower cost. This could explain the preference on d2 in risk-taking situations. As the decision maker becomes more risk taking, the preference on d2 becomes more obvious. This is consistent with the phenomena demonstrated in the figure that the expected utility and certainty equivalent of d2 becomes larger than those of d9 and d14. On the contrary, the risk averse decision maker prefers the decision alternative with lower chance to get higher cost, for example, d9 and d14. As d14 has slightly less probability of higher cost even the lower cost occurs with lower probability compared with d9, d14 becomes favorable when the decision maker becomes more risk averse.

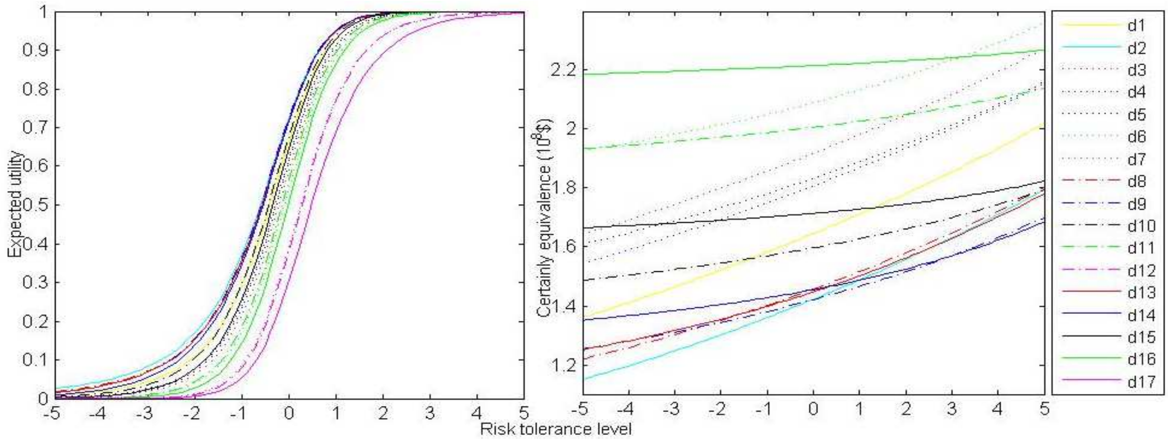


Figure 6.11 Expected utility and certainly equivalent with different risk tolerance parameter values under *WS2* (-5 to 5).

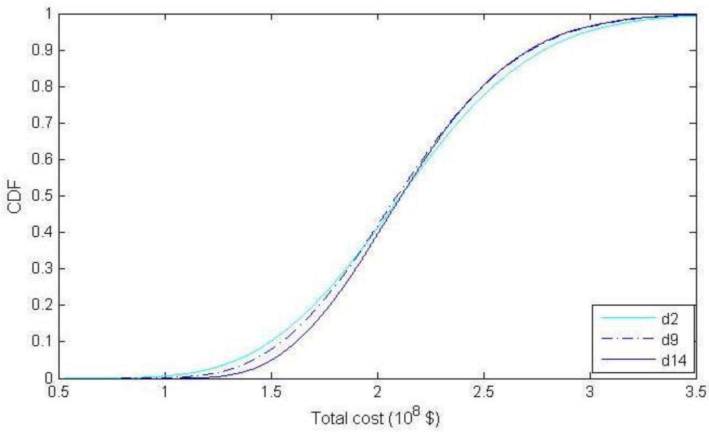


Figure 6.12 Risk profiles of outperformed decision alternatives d2, d9 and d14.

Table 6.9 shows the sensitivity analysis results to more values of the risk tolerance parameter and the probability distributions assigned to water supply, considering water demand uncertainty. The decision analysis result is more robust to the probability distributions but much more sensitive to the decision makers' risk attitudes. Under the same risk attitude, the decision result keeps the same even the probability distribution pattern changes. However, the decision result changes according to the risk tolerance parameter under the same probability distribution pattern.

Table 6.9 Sensitivity analysis of the risk attitudes

r	-5	-4	-3	-2	-1	0	1	2	3	4	5
WS1	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS2	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS3	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS4	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS5	d2	d2	d2	d2	d2	d9	d9	d14	d14	d14	d14
WS6	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS7	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14
WS8	d2	d2	d2	d2	d2	d9	d9	d9	d14	d14	d14

6.7 Discussion and Conclusions

This chapter has applied the proposed decision making framework to demonstrate the decision making process under uncertainty in the YRD, China. The decision problem focuses on matching the water supply and water demand using management measures for long-term water planning. Monetary and utility-based objective functions were identified, aiming to evaluate decisions by combing the engineering as well as decision makers' perspectives. Uncertainty analysis and the decision rules used to rank decision alternatives have been emphasized and investigated, and sensitivity analysis has been implemented to test the robustness of the decision in the decision making process.

Monetary and utility-based decision objectives have been identified to measure the consequences of decision alternatives. The monetary consequence of decision alternatives was quantified and addressed by risk profiles considering both the total cost and the corresponding probability distributions. To rank their performance, a set of risk profiles has to be compared and analyzed on the basis of minimizing the total cost. Unlike the traditional method by comparing one or two moments of the probability distributions, for instance, the mean value and the standard deviation, the information provided by the whole probability distribution was implemented using the principle of stochastic dominance. Second-order stochastic dominance test was applied considering the complexity of risk profiles, and d9 (1 new water supply project and 10% of water use efficiency improvement) outperformed others by considering the monetary consequences. The consequence of utility against the total cost was ranked based on expected utility theory. Expected utility theory defines the rational decision is the one with the maximal expected utility according to the decision maker's utility function. In addition, certainty equivalent was applied to differentiate the risk attitudes of decision makers, and discriminate the performance of decision alternatives. When considering the different risk attitudes of decision makers, the most favorable decision became d2 (1 new water supply project in 2015, and 1 new water project in 2025) when the decision maker is risk taking (r = -2). When the decision maker is risk neutral (r = 0), the most favorable decision is the same as the optimal decision considering only the monetary outcome. As the decision maker becomes risk averse (r = 2), d9 still has the maximal expected utility and the minimal certainty equivalent according to the decision maker's utility function.

The decision making process has dealt with two major types of uncertainties, outcome uncertainty and decision uncertainty (Van Asselt 2000, Xu and Booij 2004). Outcome uncertainties include (1) uncertainty from water supply conditions in the YRD due to the impact of climate change on water availability in the YRB, and the in-basin water division; (2) uncertainty from the water demand circumstances in the YRD, due to the socio-economic development and environment requirement; (3) uncertainty from the consequences of each management measure due to the input and parameters of decision models. To deal with the outcome uncertainty, scenarios of future water supply and water demand were developed using probability distributions. Scenarios attached with probability distributions express the uncertainty and the assumptions handling uncertainties explicitly and quantitatively, and the application of probability allows the updating when new information becomes available based on Bayesian theory. The probabilistic scenarios of future water supply and water demand contain a range of values as well as their chance to occur, instead of limited number of values with equal likelihood to represent the uncertain future. On the other hand, decision uncertainty was taken into account by considering and differentiating the preference and risk attitudes of decision makers in a risky context. Utility was applied to measure decision makers' preference beyond the monetary outcomes, such as satisfaction to both the total cost and the risk in the study. A negative exponential utility function was implemented to model three risk attitudes through the risk tolerance parameter. Although the decision maker is supposed to know his preference based on the axiom of expected utility theory, there is no unique utility function suitable for all decision makers' preference. The format of the utility function has to be reinvestigated and restudied in each application when facing different decision makers. The elicitation of utility functions is a complex process and has been extensively studied theoretically and practically (e.g.,Chajewska, Getoor et al. 1998, Abdellaoui 2000, Chajewska, Koller et al. 2000, Gonzales and Perny 2004).

The consideration of risk attitudes of the decision makers is useful to explain the divergent opinions and preferences of decision makers due to their different risk attitudes in the face of uncertainty. However, how to solve the disagreement among decision makers is beyond the scope of the study. Future research can be conducted to look at this interesting problem.

Sensitivity analysis has been used to test the sensitivity of decisions when the values or probability distributions of the input or the parameters are changed in the decision models. Sensitivity analysis focused on the probability distributions attached to the future water supply and water demand scenarios, market price of the management measures which are beyond the control of decision makers, and the risk tolerance levels of decision makers. Four parametric probability distributions were chosen to be attached to the water supply scenarios, in order to test the sensitivity of decision making results to the probability distribution patterns. The result shows that the patterns of probability distributions have almost no impact on the final decision. The water demand scenarios in a deterministic way and probabilistic way produced different decision making results when the decision maker is risk taking. However, to consider the uncertainty of future water demand instead of using a single trend helps decision makers to build confidence, as the decision is more robust against a large set of futures instead of a single one. The result under the probabilistic water demand scenarios is more plausible and robust against the uncertain futures. The differentiation of preference and risk attitudes of decision makers leads to the various choices of optimal decision, which can be explained as whether the decision makers' willing to take the risk with higher probability of higher cost, in order to have more chance to achieve much lower cost. Finally, the decision result is more sensitive to the market price of the management measures and then risk attitude levels of decision makers, compared with the probability distribution patterns assigned to the water supply scenarios.

In short, the study tried to deal with the decision making problem from both the perspective of engineers and decision makers. It managed to explain one of the reasons why it is difficult to achieve consensus in a collective decision making from the risk point of view in an uncertain context. Additionally, this study focused on the analysis of two important uncertainty sources using the probabilistic scenarios-based approach and sensitivity analysis. Especially, the probabilistic scenario-based approach has combined the strength from the existing classic decision making and traditional scenario planning. Other uncertainties are out of the scope of the study, such as uncertainties in the communication process to the decision makers. However, it is essential to realize the importance and essential to communicate and present the decision results to the decision makers, and future work is required to take it into account. Decision making in water resources planning and management is complex in real life as uncertainty is unavoidable, the developed decision making framework has provided a feasible way to cope with uncertainty as well as making decisions as plausible and robust as possible against the uncertain futures.

Chapter 7 Conclusions and Recommendations

7.1 Conclusions

This thesis describes uncertainty management and decision making under uncertainty for water resources planning and management. Uncertainty always exists in the decision making process and complicates it. The study provides answers to the two research questions raised in the introduction: *(1) How to develop scenarios for future water circumstances to cope with uncertainty? (2) How to make robust and rational decisions based on the developed scenarios?* What I contributed to answering these two questions are:

(1) Uncertainties from hydro-climatic, socio-economic, and institutional variables were studied. Scenarios were developed to cope with uncertainty both qualitatively and quantitatively. Unlike traditional scenario development, probability distributions were attached to quantitative scenarios in order to address uncertainty completely and explicitly. Chapter 2 reviewed studies and methods for scenario development, and argued the necessity of attaching probabilistic information to scenarios. Probabilistic scenarios were developed and applied to estimate future climatic variables in the Yellow River Basin (Chapter 3), and project driving forces of future water demand in the Yellow River Delta (Chapter 4), respectively.

(2) A probabilistic scenario-based decision making framework was developed, which emphasizes uncertainty management and decision making, and aims at robust and rational decisions under uncertainty by including a large set of scenarios with associated probabilities, as opposed to the use of deterministic predictions (Chapter 5). The proposed framework was built on the basis of probabilistic scenario development and decision theory. The framework integrates the strengths of three existing decision-making methods applied in water resources management while avoiding their disadvantages. In Chapter 6, the proposed decision making framework was applied to choose the most cost-effective and favourable water management policy for matching future water supply and water demand in the Yellow River Delta.

The main contribution of the thesis was to add probabilistic information to scenario development, and apply it to develop water scenarios in the Yellow River Basin and Yellow River Delta. As assignment of probabilities typically is a subjective process, use of reference methods and proper documentation of procedures is essential. This was demonstrated in Chapter 3, where probabilistic climate scenarios were developed using the Principle of Maximum Entropy (*POME*), which selects the probability distribution with maximal entropy (largest uncertainty) given available knowledge. This provides a reason to prefer one probability distribution on the others. Besides uncertainty related to future climate change, uncertainty from the applied hydrological model was not negligible. The propagation of uncertainty from the climatic driving forces and the applied hydrological model to future runoff was quantified using the Markov Chain Monte Carlo (*MCMC*) sampling. Regarding contributions of each uncertainty source to the total uncertainty, it was found that uncertainty from the climate variables contributes more than the model parameters, but is similar to uncertainty due to hydrological model structure and parameters. It was important to consider the uncertainty from both climate change and hydrological model since they are both significant.

Chapter 4 developed a scenario-based expert elicitation framework to probabilistically explore the driving forces of future water demand. The well-established SHELF method was applied to estimate the prior probability distributions of the driving forces on basis of the scenario storylines. Following the GBN matrix approach, four storylines comprising two extremes (urbanization speed-up/ agriculture intensive, water-saving/ water consumptive) were constructed to describe the future development of the YRD. Estimates from three water experts were aggregated into a single probability distribution using the simple linear pooling approach. The Gaussian copula was used to model the dependence among the driving forces. Uncertainty from all driving forces was propagated to future water demand using *MCMC* sampling. Instead of being presented with limited discrete values, future water demand was quantified using continuous probability distributions, covering a wide range of possible future alternatives.

Following probabilistic scenario development, another contribution of the thesis was the development of a systematic decision making framework to support robust and rational decision making under uncertainty. The framework not only investigated the monetary objective, but also further engaged the decision makers by investigating their preferences and risk attitudes (risk averse, risk neutral, risk taking) under uncertainty. Decision making is not only about choosing a decision, but also about why the decision is chosen by the decision maker, and why disagreements could exist within a group of decision makers. Although consideration of their preference and risk attitudes could not provide a prescriptive guide for decision making, it could help to explain, and even predict the behaviour of decision makers. The application of maximum expected utility theory allows the engagement of decision makers' preference and risk attitudes. To compare the economic outcomes of decision alternatives, the entire distribution of costs and utilities, rather than one or two moments, were taken into account, and alternatives were ranked using stochastic dominance tests. In Chapter 6, 17 management measures were proposed to fill the water shortage gap in the YRD for the next 30 years. Monetary and utility-based objective functions were identified, thus combining the engineering as well as decision makers' perspectives. A negative exponential utility function was implemented to model three risk attitudes using the risk tolerance parameter. In the decision making process, sensitivity analysis was implemented to test the robustness of decision alternatives given uncertainty from water supply, water demand, market price of management measures, and the preference from decision makers. The sensitivity analysis showed that the decision result is more sensitive to the market price of the management measures and risk attitudes of decision makers, than to the probability distribution patterns assigned to the water scenarios.

7.2 Future directions and researches

Eight recommendations are proposed for future research on scenario development and decision making in water resources planning and management.

(1) The proposed Bayesian framework in probabilistic scenario development has great potential in future scenario development exercises. Instead of assigning probability distributions objectively, the Bayesian framework provides a paradigm to assign subjective priors and update to posteriors in light of new information and data. In the study, non-informative priors were assigned for the climate variables, and information about climate change from GCMs was used to update the probability distributions. Bayesian probabilities add numerical values to scenarios; however, there are challenges to apply Bayesian probabilities for scenario development: such as knowledge requirement about probabilities and Bayesian theory, and sufficient resources requirement such as time, information, computation and research. For example, the application of the probability update is complicated, as to obtain new data or information is sometimes expensive and time-consuming, to estimate the conditional probabilities requires scenario developers to be highly explicit and clear about their assumptions, or the likelihood function is difficult to estimate or interpret. Future research should be carried out to better understand and implement Bayesian probabilities in scenario development.

(2) More research has to be carried out to increase the credibility and reliability of expert elicitation in probabilistic scenario development. Expert elicitation can be used to estimate priors and the likelihood functions when hard data is not available or limited. Usually, experts need to be carefully selected and trained, and they are supposed to be calibrated to show their ability to express their knowledge. In this study, the experts were not calibrated in advance of the water demand scenarios development exercise, but they were asked to provide feedback and revision of their judgement iteratively using an existing method (SHELF). Expert elicitation can provide important inputs for scientific research and real-life applications, while more research has to be carried out to increase its credibility and reliability. Another issue with expert elicitation is the aggregation of the opinions of multiple experts; neither mathematical approaches such as Bayesian paradigm nor behaviour approaches can perfectly solve the problem. Future research should be done to develop better mathematical models and behaviour aggregation procedures to improve the performance.

(3) The rainfall-runoff model applied to simulate the hydrological process in the YRB should be improved. Considering the large area of the YRB and its heterogeneous characteristics of the hydrological parameters (land use, soil moisture, evaporation, etc.), the YRB should be divided into several sub-basins when simulating the hydrological process. In future research, spatial variability should be included in the modelling process in order to better understand and model the hydrological processes.

(4) Further investigations should be implemented to weigh the GCMs prediction performance when estimating the probability distributions of the hydro-climatic variables. The hydro-climatic variables, as input for the hydrological model, were downscaled outputs from multiple GCMs and IPCC emission scenarios. In the analysis, all downscaled climate scenarios were assumed to be equally weighted. The uncertainty due to different downscaling techniques is difficult to be determined. The performance of the GCMs is different due to the different assumptions about climate model parameters and structures, and should be weighted differently in future work.

(5) Decision makers should be engaged more in decision analysis. Decision makers were involved by explicitly indicating and measuring their preference and risk attitudes. The risk attitudes were simply modelled by a negative exponential utility function. Their preference of the decision alternatives were measured and compared by expected utility. In reality, no single utility

function can objectively represent the decision makers' preference and risk attitudes. There have been a number of studies to elicit utility functions (e.g.,Chajewska, Getoor et al. 1998, Abdellaoui 2000), which have not been widely applied in decision making problems in water resources planning and management. Although expected utility theory, as a simplification and abstraction of reality, has been challenged not to represent the complex and usually 'irrational' human behaviours, to investigate the complex human behaviours is out of the study scope. However, future research should pay more attention to study the characteristics and behaviours of decision makers, in order to elicit the utility functions which can closely represent and interpret their preferences.

(6) Adaptive water management should not be a trendy concept but a pragmatic guide. Adaptive water resources management is more flexible and dynamic to deal with uncertainty and surprise, as it allows the change of decisions after new information is obtained or new lessons are learned from past experience, since adaptive water management is a 'learning through doing' process (Slinger, Huizinga et al. 2005). Although the proposed decision making framework did not explicitly emphasize an adaptive process, it is meant to support an iterative and repetitive decision making, when scenarios are diverging from expected trajectories, or new decision alternatives have to be proposed and evaluated under the framework. In order to support adaptive water management, continuous monitoring and comparison of developed scenarios and future reality is required for scenario updating.

(7) A large effort in decision making research has been made to understand and analyse uncertainty, and more effort should also be made to communicate uncertainty among scientists, experts, decision makers, and stakeholders. Besides scientific research conducted by scientists and experts, the participation of stakeholders and decision makers let them contribute local knowledge and expectations to scenario development in face of uncertainty. Communicating uncertainty is also helpful for the public and the decision makers to realize the potential risks associated with uncertainty. Articulating uncertainty to the public without technical background is a challenge, but it is essential for a transparent and participatory water resources management.

(8) Water shortage in the YRD is likely to become worse, due to the impact of climate change, population growth, economic development, water competition upstream, etc. Water supply in the YRD is heavily dependent on the YRB. However, the water shortage situation in the YRB is

already severe enough. The available water allocated to the YRD is not likely to meet its increasing water demand and socio-economic development. The thesis mainly investigated the technical measures to manage water supply and demand, such as building new water projects and investing in water saving technologies. The effect of these measures to relieve water shortage is significant and rapid, but large monetary and labour investment is required to implement them. However, non-technical measures are believed to help in relieving the problem in a low-cost and high-impact way. For example, increasing the public awareness and participation of water-saving through education, adjusting water prices (the water price for irrigation is very low while its water demand is high in the YRD) to stimulate more efficient water use, promoting rain harvest technology for each household, etc (Savenije and Van Der Zaag 2002). In practice, an optimal combination of technical and non-technical water management is required to relieve the water shortage problems and maintain socio-economic development.

Bibliography

2030WaterResourcesGroup (2009). Charting our water future Economic frameworks to inform decision-making. Available at: www.2030waterresourcesgroup.com, 2030 Water Resources Group.

Abdellaoui, M. (2000). "Parameter-free elicitation of utility and probability weighting functions." Management Science 46(11): 1497-1512.

Abrams, K., J. Myles and D. Spiegelhalter (2004). Bayesian approaches to clinical trials and health-care evaluation, Wiley, Chichester, UK.

Alcamo, J. (2008). Chapter Six The SAS Approach: Combining Qualitative and Quantitative Knowledge in Environmental Scenarios. Developments in Integrated Environmental Assessment. A. Joseph, Elsevier. Volume 2: 123-150.

Alcamo, J. and G. Gallopín (2009). Building a 2nd Generation of World Water Scenarios: Water in a Changing World. The United Nations World Water Development Report 3. Paris, United Nations World Water Assessment Programme (WWAP).

Allais, M. (1953). "Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école Américaine." Econometrica: Journal of the Econometric Society: 503-546.

Ames, D. P., B. T. Neilson, D. K. Stevens and U. Lall (2005). "Using Bayesian networks to model watershed management decisions: an East Canyon Creek case study." Journal of Hydroinformatics: 267-282.

Arnell, N. W. (1999). "Climate change and global water resources." Global Environmental Change 9: 31-49.

Arnell, N. W. (2004). "Climate change and global water resources: SRES emissions and socio-economic scenarios." Global Environmental Change 14: 31-52.

Ascough Ii, J. C., H. R. Maier, J. K. Ravalico and M. W. Strudley (2008). "Future research challenges for incorporation of uncertainty in environmental and ecological decision-making." Ecological Modelling 219(3–4): 383-399.

Austin, P. C. and J. V. Tu (2004). "Bootstrap methods for developing predictive models." The American Statistician 58(2): 131-137.

Axelrod, R., Ed. (1976). Structure of Decision: The Cognitive Maps of Political Elites Princeton, N J., Princeton University Press.

Beck, L. and T. Bernauer (2010). Water Scenarios for the Zambezi River Basin, 2000-2050. Climate Change and Security.

Bhat, C. R. and N. Eluru (2009). "A copula-based approach to accommodate residential self-selection effects in travel behavior modeling." Transportation Research Part B: Methodological 43(7): 749-765.

Bishop, P., A. Hines and T. Collins (2007). "The current state of scenario development: an overview of techniques." Foresight 9(1): 5-25.

Börjeson, L., M. Höjer, K. H. Dreborg, T. Ekvall and G. Finnveden (2006). "Scenario types and techniques: Towards a user's guide." Futures 38(7): 723-739.

Bryant, B. P. and R. J. Lempert (2010). "Thinking inside the box: A participatory, computer-assisted approach to scenario discovery." Technological Forecasting and Social Change 77(1): 34-49.

Buytaert, W., M. Vuille, A. Dewulf, R. Urrutia, A. Karmalkar and R. Celleri (2010). "Uncertainties in climate change projections and regional downscaling: implications for water resources management." Hydrology and Earth System Sciences 7: 1821-1848.

Calder, I. R. (1998). Water resource and land use issues, IWMI.

Carpenter, S. R., P. L. Pingali, E. M. Bennett and M. B. Zurek, Eds. (2005). Ecosystems and Human Well-Being: Volume 2 Scenarios: Findings of the Scenarios Working Group (Millennium Ecosystem Assessment Series). Washington, Island Press. Available onlin at: http://www.watercouncil.org.

Carter, T. R., R. N. Jones and X. F. Lu, Eds. (2007). New assessment methods and the characterization of future conditions. Climate Change 2007: Impacts, Adaptation, and Vulnerability. Cambridge, UK, Cambridge University Press,133-171.

Castelletti, A. and R. Soncini-Sessa (2007). "Bayesian Networks and participatory modelling in water resource management." Environmental Modelling & Software 22(8): 1075-1088.

Cenacchi, N., Z. X. Xu, W. Yu and C. Ringler (2011). Impact of Global Change on Large River Basins: Example of the Yellow River Basin, International food policy research institute.

Chajewska, U., L. Getoor, J. Norman and Y. Shahar (1998). Utility elicitation as a classification problem. Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers Inc.

Chajewska, U., D. Koller and R. Parr (2000). Making rational decisions using adaptive utility elicitation. AAAI/IAAI.

Charlton, M. B. and N. W. Arnell (2011). "Adapting to climate change impacts on water resources in England—An assessment of draft Water Resources Management Plans." Global Environmental Change 21(1): 238-248.

Chermack, T. J., S. A. Lynham and W. E. A. Ruona (2001). "A review of scenario planning literature." Futures Research Quarterly Summer: 7-31.

Cherubini, U., E. Luciano and W. Vecchiato, Eds. (2004). Copula Methods in Finance. Hoboken, NJ, John Wiley and Sons.

Chhibber, S., G. Apostolakis and D. Okrent (1992). "A taxonomy of issues related to the use of expert judgments in probabilistic safety studies." Reliability Engineering & System Safety 38(1–2): 27-45.

ChinaGovernment (1994). China's Agenda 21: White book for China's Population, Environment and Development in the 21 Century. Beijing: 1-192.

Chowdhury, R. and R. Rahman (2008). "Multicriteria decision analysis in water resources management: the malnichara channel improvement." Int. J. Environ. Sci. Tech 5(2): 195-204.

Choy, S. L., R. O'Leary and K. Mengersen (2009). "Elicitation by design in ecology: using expert opinion to inform priors for Bayesian statistical models." Ecology 90(1): 265-277.

Chung, S. O., J. A. Rodri´Guez-di´az, E. K. Weatherhead and J. W. Knox (2010). "Climate change impacts on water for irrigation paddy rice in South Korea." Irrigation and Drainage 60: 263-273.

Clayton, D. G. (1978). "A model for association in bivariate life tables and its application in epidemiological studies of familial tendency in chronic disease incidence." Biometrika 65(1): 141-151.

Clemen, R. T., G. W. Fischer and R. L. Winkler (2000). "Assessing dependence: Some experimental results." Management Science 46(8): 1100-1115.

Clemen, R. T. and T. Reilly (1999). "Correlations and copulas for decision and risk analysis." Management Science 45(2): 208-224.

Clemen, R. T. and R. L. Winkler (1985). "Limits for the precision and value of information from dependent sources." Operations Research 33(2): 427-442.

Clemen, R. T. and R. L. Winkler (1999). "Combining probability distributions from experts in risk analysis." Risk Analysis 19(2): 187-203.

CMWR (2002). Annual reports from major river basins in 2001.Chinese Ministry of Water Resources. Beijing:CMWR.

Collins, W. D., C. M. Bitz, M. L. Blackmon and G. B. Bonan, et al. (2005). "The Community Climate System Model (CCSM)." Journal of Climate(special issue).

Cooke, R. M. (2013). "Validating Expert Judgment with the Classical Model." Experts and Consensus in Social Science - Critical Perspectives from Economics, Sociology, Politics, and Philosophy.

Cosgrove, W. J. and F. R. Rijsberman, Eds. (2000). World Water Vision: Making Water Everybody's Business. London, Earthscan Publications.Available online:http://www.worldwatercouncil.org.

Davis, W. Y. (2003). Water demand forecast methodology for California water planning areas-work plan and model review, Planning and Management Consultants.

de Kort , I. A. T. and M. J. Booij (2007). "Decision making under uncertainty in a decison support system for the Red River." Environmental Modelling & Software 22: 128-136.

Deltares (2009). Towards sustainable development of deltas, estuaries and coastal zones : Description of eight selected deltas.

Dessai, S. and M. Hulme (2004). "Does climate policy need probabilities." Climate Policy 4(2): 107-128.

Dessai, S. and M. Hulme (2007). "Assessing the robustness of adaptation decisions to climate change uncertainties: A case study on water resources management in the East of England." Global Environmental Change 17(1): 59-72.

Dessai, S. and J. P. van der Sluijs (2011). "Modelling climate change impacts for adaptation assessments." Simplicity, Complexity and Modelling: 83-102.

Doll, P. (2004). Environmental challenges in the mediterranean 2000-2050

Dong, C. L., G. Schoups and N. Van de Giesen (2012). Characterizing uncertainty of hydro-climatic variables for water managementin the YellowRiver Basin: Learning from the past. the 5th International Yellow River Forum, Zhengzhou, China.

Dong, C. L., G. Schoups and N. van de Giesen (2013). "Scenario development for water resource planning and management: A review." Technological Forecasting and Social Change 80(4): 749-761.

Duchness, S., M. B. Beck and A. L. Reda (2001). "Ranking stormwater control strategies under uncertainty: the River Cam case study." Water Sci. Technol. 43: 311-320.

Eckhardt, K. and U. Ulbrich (2003). "Potential impacts of climate change on groundwater recharge and streamflow in a central European low mountain range." Journal of Hydrology 284(1–4): 244-252.

Ercin, A. E. and A. Y. Hoekstra (2012). Water footprint scenarios for 2050, UNESCO-IHE Institute for Water Education, Delft.

Falloon, P. and R. Betts (2010). "Climate impacts on European agriculture and water management in the context of adaptation and mitigation—The importance of an integrated approach." Science of The Total Environment 408(23): 5667-5687.

Fang, H.-B., K.-T. Fang and S. Kotz (2002). "The Meta-elliptical Distributions with Given Marginals." Journal of Multivariate Analysis 82(1): 1-16.

Fenicia, F., H. H. G. Savenije, P. Matgen and L. Pfister (2007). "A comparison of alternative multiobjective calibration strategies for hydrological modeling." Water Resources research 43(W03434): 1-16.

Ferrell, W. R. (1985). Combining Individual Judgments. Behavioral Decision Making. G. Wright, Springer US: 111-145.

Figueira, J., S. Greco and M. Ehrgott (2005). Multiple criteria decision analysis—State of the art survey, Springer Science and Business Media Inc.

Fischer, G., F. N. Tubiello, H. van Velthuizen and D. A. Wiberg (2007). "Climate change impacts on irrigation water requirements: Effects of mitigation, 1990–2080." Technological Forecasting and Social Change 74(7): 1083-1107.

Fischhoff, B. (2003). "Hindsight≠ foresight: the effect of outcome knowledge on judgment under uncertainty." Quality and Safety in Health Care 12(4): 304-311.

Flörke, M. and J. Alcamo (2004). European Outlook on Water Use, Center for Environmental Systems Research University of Kassel.

Frank, M. J. (1979). "On the simultaneous associativity ofF (x, y) andx+y− F (x, y)." Aequationes Mathematicae 19(1): 194-226.

Frees, E. W. and P. Wang (2005). "Credibility using copulas." North American Actuarial Journal 9(2): 31-48.

French, S. (1981). "Consensus of opinion." European Journal of Operational Research 7: 332-340.

Frühwirth-Schnatter, S. (2006). Finite Mixture and Markov Switching Models. New York, Springer.

Gallopín, G. (2012). Five stylized scenarios. Paris, France, United Nations Educational, Scientific and Cultural Organization.

Gallopín, G. C. and F. Rijsberman (2000). "Three Global Water Scenarios." International Journal of Water 1.

Garthwaite, P. H., J. B. Kadane and A. O'hagan (2005). "Statistical methods for eliciting probability distributions." Journal of the American Statistical Association 100(470): 680-701.

Garvey, P. R. (2008). Analytical Methods for Risk Management: A Systems Engineering Perspective, Taylor & Francis.

Gay, C. and F. Estrada (2009). "Objective probabilites about future climate are a matter of opinon." Climate change 99: 27-46.

Genest, C. and A.-C. Favre (2007). "Everything you always wanted to know about copula modeling but were afraid to ask." Journal of Hydrologic Engineering 12(4): 347-368.

Genest, C. and K. J. McConway (1990). "Allocating the weights in the linear opinion pool." Journal of Forecasting 9(1): 53-73.

Genest, C. and L.-P. Rivest (1993). "Statistical inference procedures for bivariate Archimedean copulas." Journal of the American statistical Association 88(423): 1034-1043.

Genest, C. and M. J. Schervish (1985). "Modeling expert judgements for Bayesain updating." Annuals of Statistics 13: 1198-1212.

Girod, B., A. Wiek, H. Mieg and M. Hulme (2009). "The evolution of the IPCC's emissions scenarios." Environmental Science & Policy 12(2): 103-118.

Gleick, P. H., H. Cooley and D. Groves (2005). California water 2030: An efficient future. Okland, the Pacific Institute.

Gokhale, D. and S. J. Press (1982). "Assessment of a prior distribution for the correlation coefficient in a bivariate normal distribution." Journal of the Royal Statistical Society. Series A (General): 237-249.

Gonzales, C. and P. Perny (2004). "GAI Networks for Utility Elicitation." KR 4: 224-234.

Gonzalez, J. S., M. B. Payán and J. M. Riquelme-Santos (2012). "Optimization of wind farm turbine layout including decision making under risk." Systems Journal, IEEE 6(1): 94-102.

Gordon, C., C. Cooper, C. A. Senior, H. Banks, J. M. Gregory, T. C. Johns , J. F. B. Mitchell and R. A. Wood (2000). "The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without fux adjustments." Climate Dynamics 16: 147-168.

Gordon, H. B., L. D. Rotstayn, J. L. McGregor, M. R. Dix, E. A. Kowalczyk, S. P. O'Farrell, L. J. Waterman, A. C. Hirst, S. G. Wilson, M. A. Collier, I. G. Watterson and T. I. Elliott (2002). The CSIRO Mk3 Climate System Model CSIRO Atmospheric Research (CSIRO Atmospheric Research technical paper; no. 60): 130pp.

Groves, D. G. (2006). New methods for identifying robust long-term water resources management strategies for california.

Groves, D. G., D. Knopman, R. J. Lempert, S. H. Berry and L. Wainfan (2008). Presenting uncertainty about climate change to water-resource managers, Rand Corporation.

GWP (2000). "Main article focuses on IWRM concepts. ." GWP Newsflow 2/00.

Haasnoot, M. and H. Middelkoop (2012). "A history of futures: A review of scenario use in water policy studies in the Netherlands." Environmental Science & Policy 19–20(0): 108-120.

Hasumi, H. and S. Emori (2004). K-1 Coupled GCM (MIROC) Description. K-1 Technical Report No. 1, CCSR, NIES and FRCGC.

Higgins, H., I. Dryden and M. Green (2012). A Bayesian approach demonstrating that incorporation of practitioners' clinical beliefs into research design is crucial for effective knowledge transfer. Udder Health and Communication, Springer: 133-140.

Higgins, H., I. Dryden and M. Green (2012). "A Bayesian elicitation of veterinary beliefs regarding systemic dry cow therapy: Variation and importance for clinical trial design." Preventive Veterinary Medicine 106(2): 87-96.

Higham, N. J. (2002). "Computing the nearest correlation matrix—a problem from finance." IMA Journal of Numerical Analysis 22(3): 329-343.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones and A. Jarvis (2005). "Very high resolution interpolated climate surfaces for global land areas." International Journal of Climatology 25: 1965-1978.

Hoekstra, A. Y. (1998). Perspectives on Water: An Integrated Model-based Exploration of the Future PhD thesis, Delft University of Technology.

Hoekstra, A. Y. (2000). "Appreciation of water: four perspectives." Water Policy 1(6): 605-622.

Hoekstra, A. Y., A. K. Chapagain, M. M. Aldaya and M. M. Mekonnen (2011). The water footprint assessment manual - Setting the global standard. London, UK Earthscan.

Hoekstra, A. Y., M. M. Mekonnen, A. K. Chapagain, R. E. Mathews and B. D. Richter (2012). "Global monthly water scarcity: blue water footprints versus blue water availability." PLoS One 7(2): e32688.

Huang, D., T. Chen and M.-J. J. Wang (2001). "A fuzzy set approach for event tree analysis." Fuzzy Sets and Systems 118(1): 153-165.

Hulme, M. and S. Dessai (2008). "Negotiating future climates for public policy: a critical assessment of the development of climate scenarios for the UK." Environmental Science & Policy 11: 54-70.

Huss, W. R. and E. J. Honton (1987). "Scenario planning-what style should you use?" long Range Planning 20(4): 21-29.

Iital, A., V. Voronova and M. Klõga (2011). "Development of water scenarios for large lakes in Europe: the case of Lake Peipsi." Journal of Water and Cliamte change: 154-165.

IPCC (1990). Emissions scenarios. Response Strategies Working Group (Ed.), IPCC.

IPCC (1992c). Emission scenarios for IPCC: an update- Assumptions, Methodoligy, and Results. W. J. Pepper, Leggett, J., Swart, R.J. , Wasson,J.,Edmonds,J., Minzer,I. (Eds.). Geneva.

IPCC (2000). Special report on emissions scenarios. N. Nakicenovic, Swart, R. (Eds.). Cambridge University Press, Cambridge.

IPCC (2007). IPCC Fourth Assessment Report: Climate Change 2007 (AR4). Working Group II Report"Impacts, Adaptation and Vulnerability'. Cambridge, United Kingdom and New York, NY, USA.

IPCC (2007). Working Group III Report " Mitigation of Climate Change". Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007 O. R. D. B. Metz, P.R. Bosch, R. Dave, L.A. Meyer (eds). Cambridge, United Kingdom and New York, NY, USA.

IPCC (2008). Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies. R. Moss, Babiker, M., Brinkman, S., Calvo, E.,Carter, T., Edmonds, J., Elgizouli, I., Emori, S., Erda, L.,Hibbard, K., Jones, R., Kainuma, M., Kelleher, J., Lamarque,J.F., Manning, M., Matthews, B., Meehl, J., Meyer, L., Mitchell,J., Nakicenovic, N., O'Neill, B., Pichs, R., Riahi, K., Rose, S.,Runci, P., Stouffer, R., Vuuren, D.v., Weyant, J., Wilbanks, T.,Ypersele, J.P.v., Zurek, M. (Eds.),. Geneva, IPCC.

Jayakrishnan, R., R. Srinivasan, C. Santhi and J. G. Arnold (2005). "Advances in the application of the SWAT model for water resources management." Hydrological Processes 19: 749-762.

Jaynes, E. T. (1957). "Information theory and statistical mechanics." The Physical review 106(4): 620-630.

Johns, T. C., C. F. Durman, H. T. Banks, M. J. Roberts and A. J. McLaren (2006). "The new Hadley Centre climate model HadGEM1: Evaluation of coupled simulations." Journal of Climate 19(7): 1327-1353.

Johnson, N. L. and S. Kott (1975). "On some generalized Farlie-Gumbel-Morgenstern distributions." Communications in Statistics-Theory and Methods 4(5): 415-427.

Jouini, M. N. and R. T. Clemen (1996). "Copula models for aggregating expert opinions." Operations Research 44(3): 444-457.

Jugnclaus, J. H., M. Botzet, H. Haak, N. Keenlyside, J.-J. Luo, M. Latif, J. Marotzke, U. Mikolajewics and E. Roeckner (2006). "Ocean circulation and tropical variability in the AOGCM ECHAM5/MPI-OM." Journal of Climate 19(16).

Kahn, H., Ed. (1962). Thinking about the unthinkable. New York, Horizon Press.

Kahneman, D. and A. Tversky (1979). "Prospect theory: An analysis of decision under risk." Econometrica: Journal of the Econometric Society: 263-291.

Kahneman, D. and A. Tversky (1982). "Variants of uncertainty." Cognition 11(2): 143-157.

Keeney, R. L. and E. F. Wood (1977). "An illustrative example of the use of multiattribute utility theory for water resource planning." Water Resorces Research 13(4): 705-712.

Kelly, K. and R. Krzysztofowicz (1997). "A bivariate meta-Gaussian density for use in hydrology." Stochastic Hydrology and Hydraulics 11(1): 17-31.

Kendall, M., Ed. (1948). Rank Correlation methods. London, Charles Griffin and Company limited.

King, J., C. Brown and H. Sabet (2003). "A scenario-based holistic approach to environmental flow assessments for rivers " River research and applications 19: 619-639.

Kinnersley, N. and S. Day (2013). "Structured approach to the elicitation of expert beliefs for a Bayesian-designed clinical trial: a case study." Pharmaceutical statistics.

Kodikara, P. N. (2008). Multi-objective optimal operation of urban water supply systems, Victoria University, Australia.

Kok, K. and M. van Vliet (2011). "Using a participatory scenario development toolbox: added values and impact on quality of scenarios." Journal of Water and Cliamte change 32: 87-105.

Kok, K., M. van Vliet, I. Bärlund, A. Dubel and J. Sendzimir (2011). "Combining participative backcasting and exploratory scenario development: Experiences from the SCENES project." Technological Forecasting and Social Change 78(5): 835-851.

Korteling, B., S. Dessai and Z. Kapelan (2013). "Using information-gap decision theory for water resources planning under severe uncertainty." Water Resources Management 27(4): 1149-1172.

Kosko, B. (1986). "Fuzzy cognitive maps." International Journal of MAn-Machine Studies 24(1): 65-75.

Kouvelis, P. and G. Yu (1997). Robust discrete optimization and its applications, Springer.

Krueger, T., T. Page, K. Hubacek, L. Smith and K. Hiscock (2012). "The role of expert opinion in environmental modelling." Environmental Modelling & Software 36(0): 4-18.

Kruskal, W. (1958). "Ordinal measures of association." J. Am. Statist. Assoc., 53: 814-861.

Krzysztofowicz, R. (1983). "Strength of preference and risk attitude in utility measurement." Organizational Behavior and Human Performance 31(1): 88-113.

Kurowicka, D. and R. M. Cooke (2006). Uncertainty analysis with high dimensional dependence modelling, Wiley.

Kynn, M. (2008). "The 'heuristics and biases' bias in expert elicitation." Journal of the Royal Statistical Society: Series A (Statistics in Society) 171(1): 239-264.

Lempert, R. J. and D. G. Groves (2010). "Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west." Technological Forecasting and Social Change 77(6): 960-974.

Lempert, R. J., D. G. Groves, S. W. Popper and S. C. Bankes (2006). "A general, analytic method for generating robust strategies and narrative scenarios." Management Science 52(4): 514-528.

Lempert, R. J., S. W. Popper and S. C. Bankes (2003). Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. Santa Monica, California, RAND: 187pp.

Lévite, H., H. Sally and J. Cour (2003). "Testing water demand management scenarios in a water-stressed basin in South Africa: application of the WEAP model." Physics and Chemistry of the Earth, Parts A/B/C 28(20-27): 779-786.

Levy, H. (1992). "Stochastic dominance and expected utility: survey and analysis." Management Science 38(4): 555-593.

Li, F. L., M. Y. Fan, J. Liu, H. W. Chen and H. J. Liu (2011). Report on optimal allocation of water resources and adaptive water management in the Yellow River Delta, Shandong Water Resource Research Institute (in Chinese).

Li, L., Z. C. Hao, J. H. Wang, Z. H. Wang and Z. B. Yu (2008). "Impact of future climate change on runoff in the head region of the Yellow River." Journal of Hydrologic engineering: 347-354.

Li, R. C. (2008). Application of equity principles of IWRM in water allocation in the Yellow River Basin PhD dissertation, Delft University of Technology.

Li, Y. P., J. Yuan, L. J. Liu and M. Z. Fu (1999). Vulnerability assessment of the Yellow River Delta to predicted climate change and sea level rise. Vulnerability assessment of two major wetlands in the Asia-Pacific region to climate change and sea level rise. R. A. van Dam, Finlayson, C. M., & Watkins, D. Darwin, Australia, Supervising Scientist: 7-73.

Liu, Y., M. Mahmoud and H. Hartmann (2008). "Formal scenario development for environmental impact assessment studies." Environmental modelling, software and decison support: state of the art and new perspectives

Liuzzo, L., L. V. Noto, E. R. Vivoni and G. La Loggia (2010). "Basin-Scale Water Resources Assessment in Oklahoma under Synthetic Climate Change Scenarios Using a Fully Distributed Hydrologic Model." JOURNAL OF HYDROLOGIC ENGINEERING 2010: 107-122.

Loucks, D. P., E. Van Beek, J. R. Stedinger, J. P. Dijkman and M. T. Villars (2005). Water resources systems planning and management: an introduction to methods, models and applications, Paris: UNESCO.

Low-Choy, S., A. James, J. Murray and K. Mengersen, Eds. (2012). A User-Friendly, Interactive Tool to Support Scenario-Based Elicitation of Expert Knowledge. Expert Knowledge and Its Application in Landscape Ecology, Springer New York Dordrecht Heidelberg London.

Mahmoud, M. (2008). Scenario development for water resources decision-making. PhD.thesis, The University of Arizona.

Mahmoud, M., Y. Liu, H. Hartmann, S. Stewart, T. Wagener, D. Semmens, R. Stewart, H. Gupta, D. Dominguez, F. Dominguez, D. Hulse, R. Letcher, B. Rashleigh, C. Smith, R. Street, J. Ticehurst, M. Twery, H. van Delden, R. Waldick, D. White and L. Winter (2009). "A formal framework for scenario development in support of environmental decision-making." Environmental Modelling & Software 24(7): 798-808.

Mahmoud, M. I., H. V. Gupta and S. Rajagopal (2011). "Scenario development for water resources planning and watershed management: Methodology and semi-arid region case study." Environmental Modelling & Software 26(7): 873-885.

Markowitz, H. (1959). Portfolio selection: efficient diversification of investments, Yale university press.

Martelli, A. (2001). "Scenario building and scenario planning: state of the art and prospects of evolution." Futures Research Quarterly Summer: 57-70.

Marti, O. P., J. Braconnot, R. Bellier, S. Benshila and P. Bony (2005). The new IPSL climate system model:IPSL-CM4, Institute Pierre Simon Laplace.

McCarthy, J. J., O. F. Canziani, N. A. Leary, D. J. Dokken and K. S. White, Eds. (2001). Climate Change 2001: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge Cambridge University Press.

McIntyre, N., M. Lees, H. Wheater, C. Onof and B. Connorton (2003). "Evaluation and visualization of risk to water resources." Proc Inst Civil Eng Water Marit Eng 156(1): 1-11.

Means III, E., M. Laugier, J. Daw, L. Kaatz and M. Waage (2010). Decision support planning methods: incorporating climate change uncertainties into water planning, Malcolm Pirnie, Inc. & Denver Water.

Mendel, M. B. and T. B. Sheridan (1989). "Filtering information from human experts." Systems, Man and Cybernetics, IEEE Transactions on 19(1): 6-16.

Middelkoop, H., J. C. J. Kwadijk, W. P. A. Van Deursen and M. B. A. Van Asselt (2002). "Scenario analyses in global change assessment for water management in the lower Rhine delta." Climatic Change: Implications for the Hydrological Cycle and for Water Management: 445–463.

Millett , S. M. (2008). Should probabilities be used with scenarios. Future Associate LLC.

Mimikou, M. A., E. Baltas, E. Varanou and K. Pantazis (2000). "Regional impacts of climate change on water resources quantity and quality indicators." Journal of Hydrology 234(1–2): 95-109.

Morgan, M., H. Dowlatabadi, M. Henrion, D. Keith, R. Lempert, S. McBride, M. Small and T. Wilbanks (2009). Best Practice Approaches for Characterizing, Communicating and Incorporating Scientific Uncertainty in Climate Decision Making. U.S. Climate Change Science Program. Synthesis and Assessment Product 5.2.

Morgan, M. G. (1992). Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis, Cambridge University Press.

Morgan, M. G. and D. W. Keith (1995). "Subjective judgments by climate experts." Environmental Science & Technology 29(10): 468A-476A.

Morgan, M. G., L. F. Pitelka and E. Shevliakova (2001). "Elicitation of expert judgments of climate change impacts on forest ecosystems." Climatic Change 49(3): 279-307.

Morris, P. (1983). "An axiomatic approach to expert resolution." Management science 29: 24-32.

Morris, P. A. (1977). "Combining expert judgments: A Bayesian approach." Management Science 23(7): 679-693.

Mote, P., B. P. B. Duffy and E. Maurer (2011). Guilderlines for constructing climate scenarios. EOS,Transactions, American Geophisical Union (AGU). 92.

Muhammetoglu, A., H. Muhammetoglu, S. Oktas, L. Ozgokcen and E. Soyupak (2005). "Impact assessment of different management scenarios on water quality of porsuk river and dam system – Turkey." Water Resources Management 19: 199-210.

Myung, I. J., S. Ramamoorti and A. D. Bailey (1996). "Maximum entropy aggregation of expert predictions." Management Science 42(10): 1420-1436.

Nakicenovic, N., J. Alcamo, G. Davis and B. de Vries, Eds. (2000). Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge, U.K., Cambridge University Press.

Nawaz, N. R. and A. J. Adeloye (2006). "Monte Carlo assessment of sampling uncertainty of climate change impacts on water resources yield in Yorkshire, England." Climate change 78: 257-292.

Norstad, J. (2011). An introduction to utility function. Available online http://homepage.mac.com/j.norstad/finance/util.pdf.

North, D. W. (1968). "A tutorial introduction to decison theory." IEEE Transactions on systems science and cybernetics 4(3).

O'Hagan, A., C. E. Buck, A. Daneshkhah, J. R. Eiser, P. H. Garthwaite, D. J. Jenkinson, J. E. Oakley and T. Rakow (2006). Uncertain judgements: Eliciting experts' probabilities, Wiley.

O'Hagan, A., C. E. Buck, A. Daneshkhah, J. R. Eiser, P. H. Garthwaite, D. J. Jenkinson, J. E. Oakley and T. Rakow (2007). Uncertain Judgements: Eliciting Expert Probabilities. Chichester, John Wiley and Sons.

Oakley, J. E. (2010). Eliciting univariate probability distributions. Rethinking risk measurement and reporting 1.

Oakley, J. E. and A. O'Hagan. (2010). "SHELF: the Sheffield Elicitation Framework (version 2.0)."

Peterman, R. M. and J. L. Anderson (1999). "Decision analysis: a method for taking uncertainties into account in risk-based decision making." Human and Ecological Risk Assessment: An International Journal 5(2): 231-244.

Pinto, C. A. and P. R. Garvey (2012). Advanced risk analysis in engineering enterprise systems. Boca Raton, Taylor & Francis Group,LLC.

Porter, M. E., Ed. (1985). Competitive advantage. New York, Free Press.

Ramirez, J. and A. Jarvis (2010). "Downscaling Global Circulation Model Outputs: The Delta Method Decision and Policy Analysis Working Paper No. 1." (Available from : http://www.ccafs-climate.org/media/ccafs_climate/docs/Downscaling-WP-01.pdf).

Reckhow, K. H. (1994). "Importance of scientific uncertainty in decision making." Environmental Management 18(2): 161-166.

Reda, A. L. L. and M. B. Beck (1997). "Ranking strategies for stormwater management under uncertainty: Sensitivity analysis." Water Science and Technology 36(5): 357-371.

Ren, S. and J. E. Oakley (2012). "Assurance Calculations for Planning Clinical Trials with Time-to-event Outcomes."

Rikkonen, P., J. Kaivo-oja and J. Aakkula (2006). "Delphi expert panels in the scenario-based strategic planning of agriculture." Foresight 8(1): 66-81.

Robertson, D. and Q. J. Wang (2004). "Bayesian networks for decision analyses - an application to irrigation system selection." Australian Journal of Experimental Agriculture 44(2): 145-150.

Rosegrant, M. W., X. M. Cai and S. A. Cline (2002). Global Water Outlook to 2025:Averting an Impending Crisis. A 2020 Vision for Food, Agriculture, and the Environment Initiative. Washington,D.C., U.S.A., International Food Policy Research Institute.

Savage, L., J. (1954). The Foundations of Statistics. New york, Wiley.

Savenije, H. H. and P. Van der Zaag (2000). "Conceptual framework for the management of shared river basins; with special reference to the SADC and EU." Water policy 2(1): 9-45.

Savenije, H. H. and P. Van Der Zaag (2002). "Water as an economic good and demand management paradigms with pitfalls." Water international 27(1): 98-104.

Savenije, H. H. G., A. Y. Hoekstra and P. Zaag (2013). "Evolving water science in the Anthropocene." Hydrology and Earth System Sciences Discussions 10(6): 7619-7649.

Savenije, H. H. G. and P. Van der Zaag (2008). "Integrated water resources management: Concepts and issues." Physics and Chemistry of the Earth, Parts A/B/C 33(5): 290-297.

Schmidt, T. (2006). "Coping with copulas." Chapter forthcoming in Risk Books: Copulasfrom theory to applications in finance.

Schneider, S. H. (2001). "What is 'dangerous' climate change?" Nature 411(6833): 17-19.

Scholten, L., A. Scheidegger, P. Reichert and M. Maurer (2013). "Combining expert knowledge and local data for improved service life modeling of water supply networks." Environmental Modelling & Software 42(0): 1-16.

Schoups, G. and J. A. Vrugt (2010). "A formal likelihood function for parameter and predictive inference of hydrologic models with correlated, heteroscedastic, and non-Gaussian errors." Water Resources Research 46.

Schoups, G., J. A. Vrugt, F. Fenicia and N. C. van de Giesen (2010). "Corruption of accuracy and efficiency of Markov chain Monte Carlo simulation by inaccurate numerical implementation of conceptual hydrologic models." WATER RESOURCES RESEARCH 46(W10530): 1-12.

Schultz, M. T., K. N. Mitchell, B. K. Harper and T. S. Bridges (2010). Decision making under uncertainty, Engineer Research and Development Center, US Army Corps of Engineers.

Schwartz, P., Ed. (1991). The art of the long view:planing for a future in an uncertain world. John Wiley &Sons Ltd, West Sussex , England

Scinocca, J. F., N. A. McFarlane, M. Lazare, Li, J., and D. Plummer (2008). "The CCCma third generation AGCM and its extension into the middle atmosphere." Atmospheric Chemistry and Physics 8: 7055-7074.

Shannon, C. E. (1948). "A Mathematical Theory of Communication." The Bell System Technical Journal 27: 379-423.

Shaw, W. D. and R. T. Woodward (2008). "Why environmental and resource economists should care about non-expected utility models." Resource and Energy Economics 30(1): 66-89.

Shiau, J. T. and R. Modarres (2009). "Copula-based drought severity-duration-frequency analysisin Iran." METEOROLOGICAL APPLICATIONS 16: 481-489.

Sklar, A. (1959). "Fonctions de répartition à n dimensions et leurs marges." Publ. Inst. Statist. Univ. Paris 8: 229-231.

Slinger, J. H., P. Huizinga, S. Taljaard, L. van Niekerk and B. Enserink (2005). "From impact assessment to effective management plans: learning from the Great Brak Estuary in South Africa." Impact Assessment and Project Appraisal 23(3): 197-204.

Stewart, T. J. and L. Scott (1995). "A scenario-based framework for multicriteria decision analysis in water resources planning." Water Resources Research 31(11): 2835-2843.

Tezuka, S., H. Murata, S. Tanaka and S. Yumae (2005). "Monte Carlo grid for financial risk management." Future Generation Computer System 21: 811-821.

Thissen, W. A. and D. B. Agusdinata (2008). Handling deep uncertainties in impact assessment. IAIA'08 Conference in Perth.

Titus, J. G. and V. Narayanan (1996). "The risk of sea level rise." Climatic Change 33(2): 151-212.

Tung, Y. K., P. Y. Wang and J. C. Yang (1993). "Water resources projects evaluation and ranking under econimic uncertainty." Water Resources Management 7: 311-333.

Tung, Y. K. and J. C. Yang (1994). "Probabilistic evaluations of economic merit of water resource projects." water Resources Management 8: 203-223.

Tversky, A. and D. Kahneman (1973). "Availability: A heuristic for judging frequency and probability." Cognitive psychology 5(2): 207-232.

UNEP(2002). Global Environment Outlook 3. Nairobi.Available online at:
http://www.unep.org/geo/geo3/, UNEP.

UNEP (2007). Global Environment Outlook 4. Environment for development.

Vaché, K. B., J. M. Eilers and M. V. Santelmann (2002). "Water quality modeling of alternative agricultural scenarios in the U.S. corn belt." Journal of the American Water Resources Association 28(3): 773-787.

van Asselt, M. B. and J. Rotmans (2002). "Uncertainty in integrated assessment modelling." Climatic Change 54(1-2): 75-105.

Van Asselt, M. B. A. (2000). Perspectives on uncertainty and risk. The PRIMA approach to decision support. The Netherlands, Kluwer Academic Publishers.

van de Heijden, K., Ed. (1994). Probabilistic planning and scenario planning. Subjective probability. Baffins Lane, Chichester, England, John Wiley & Sons Ltd.

Van Vliet, M., K. Kok, A. Lasut and J. Sendzimir (2007). Report describing methodology for scenario development at pan-European and pilot Area scales. SCENES Deliverable 2.1. Wagenigen University, Wageningen . Available online at : http://www.environment.fi/syke/scenes.

Varis, O. (1997). "Bayesian decision analysis for environmental and resource management." Environmental Modelling & Software 12(2-3): 177-185.

Varis, O. and S. Kuikka (1997). "BeNe-EIA: A Bayesian approach to expert judgment elicitation with case studies on climate change impacts on surface waters." Climatic Change 37(3): 539-563.

Varum, C. A. and C. Melo (2010). "Directions in scenario planning literature- A review of the past decades." Futures 42: 355-369.

von Neumann, J. and S. Morgenstern (1947). The Theory of Games and Economic Behavior. Princeton, NJ., Princeton University Press.

von Winterfeldt, D. and W. Edwards (2007). Defining a decision analytic structure. Chapter 6 in Advances in decision analysis. Cambridge, UK, Cambridge University Press.

Vrugt, J. A., C. J. F. ter Braak, C. G. H. Dicks, B. A. Robinson, J. M. Hyman and D. Higdon (2009). "Accelerating Markov Chain Monte Carlo Simulation by Differential Evolution with Self-Adaptive Randomized Subspace Sampling." Int. J. Nonlinear Sciences and Numerical Simulation 10(3): 273-290.

Vucetic, D. and S. P. Simonovic (2011). Water resources decision making under uncertainty. London, Department of Civil and Environmental Engineering, The University of Western Ontario.

Wagener, T., Y. Liu, S. Stewart, H. Hartmann and M. Mahmoud (2006). Imagine – Scenario development for environmental impact assessment studies. Proceedings of the iEMSs Third Biennial Meeting: Summit on Environmental Modelling and Software., International Environmental Modelling and Software Society, Burlington, USA.

Watkins Jr, D. W., D. C. McKinney, L. Lasdon, S. S. Nielsen and Q. W. Martin (2000). "A scenario-based stochastic programming model for water supplies from the highland lakes." International Transactions in Operational Research 7(3): 211-230.

Webster, M., C. Forest, J. Reilly, M. Babiker, D. Kicklighter, M. Mayer, R. Prinn, M. Sarofim, A. Sokolov and P. Stone (2003). "Uncertainty analysis of climate change and policy response." Climatic change 61(3): 295-320.

Weijs, S. V. (2011). Information theory for risk-based water system operation. PhD thesis, Delft University of Technology, the Netherlands.

Weijs, S. V., G. Schoups and N. van de Giesen (2010). "Why hydrological forecasts should be evaluated using information theory." Hydrology and Earth System Sciences 7(4): 4657-4685.

Weng, S. Q., G. H. Huang and Y. P. Li (2010). "An integrated scenario-based multi-criteria decision support system for water resources management and planning - A case study in the Haihe River Basin." Expert Systems with Applications 37(12): 8242-8254.

Winkler, R. L. (1968). "The consensus of subjective probability distributions." Management Science 15(2): B-61-B-75.

Winkler, R. L. (1981). "Combining probability distributions from dependent information sources." Management Science 27(4): 479-488.

Xiong, W., I. Holman, E. Lin, D. Conway, J. H. Jiang, Y. L. Xu and Y. Li (2010). "Climate change, water availability and future cereal production in China." Agriculture, Ecosystems & Environment 135(1-2): 58-69.

Xu, Y. and M. J. Booij (2004). Appropriate models in decision support system in river basin management. Water observation and information system for decision support, Ohrid, Repubilc of Macedonnia.

Xu, Y. P., M. J. Booij and A. E. Mynett (2007). "An appropriateness framewok for the Dutch Muese decision support system." Environmental Modelling & Software 22: 1667-1678.

Xu, Y. P. and Y. K. Tung (2009). "Decision Rules for Water Resources Management under Uncertainty." Journal of Water Resources Planing and Management 135(3): 149-159.

Xu, Y. P., Y. K. Tung, J. Li and S. F. Niu (2009). "Alternative risk measure for decison-making under uncertainty in water management." Progress in Natural Science 19: 115-119.

Xu, Z. X., Y. F. Fu, L. Cheng, Y. L. Sun, T. J. Zhu and J. Z. Li (2010). Water Supply and Demand in the Yellow River Basin: Opportunities from Water Savings, International food policy research institute (IFPRI).

Xu. Y. P. and Y. K. Tung (2008). "Decision-making in water management under uncertainty." Water Resour Manage 22: 535-550.

Yang, D. W., C. Li, H. P. Hu, Z. D. Lei, S. X. Yang, T. Kusuda, T. Koike and K. Musiake (2004). "Analysis of water resources variability in the Yellow River of China during the last half century using historical data." Water Resources Research 40(6).

Yang, D. W., W. Shao, W,. and Z. Cong, T, Eds. (2010). Analysis of climate change impact on hydrology and water resources in the Yellow River Basin. Cliamte change and adaptation for water resources in Yellow River Basin,China, IHP VII Thchnical Document in Hydrology,UNESCO Office in Beijing,2010.

Yoe, C. (2004). Scenario planning literature review. Alexandria, U.S. Army Corps of Engineers Institute for Water Resources.

Yukimoto, S., A. Noda, A. Kitoh, M. Sugi, Y. Kitamura, M. Hosaka, K. Shibata, S. Maeda and T. Uchiyama (2001). "The new Meteorological Research Institute coupled GCM (MRI-CGCM2), -model climate and variability." Papers in Meteorology and Geophysics 51: 47-88.

Zacharias, I., E. Dimitriou and T. Koussouris (2005). "Integrated water management scenarios for wetland protection: application in Trichonis Lake." Environmental Modelling & Software 20(2): 177-185.

Zhang, G. H., S. H. Fu, W. H. Fang, H. Imura and X. C. Zhang (2007). "Potential effects of climate change on runoff in the yellow river basin of china." American Society of Agricultural and Biological Engineers 50(3): 911-918.

Zhovtonog, O., M. Hoffmann, V. Polishchuk and A. Dubel (2011). "New planning technique to master the future of water on local and regional level in Ukraine." Journal of Water and Cliamte change 2(2-3): 189-200.

Zhu, T. j. and C. Ringler (2012). "Climate Change Impacts on Water Availability and Use in the Limpopo River Basin." Water 4: 28-44.

Zickfeld, K., A. Levermann, M. G. Morgan, T. Kuhlbrodt, S. Rahmstorf and D. W. Keith (2007). "Expert judgements on the response of the Atlantic meridional overturning circulation to climate change." Climatic Change 82(3-4): 235-265.

Zimmer, D. M. and P. K. Trivedi (2006). "Using trivariate copulas to model sample selection and treatment effects: application to family health care demand." Journal of Business & Economic Statistics 24(1): 63-76.

Appendix

Appendix A. Scenario-based probabilistic elicitation with SHELF

The probabilistic elicitation procedure includes the SHELF methods procedure to elicit prior probabilities from experts described in section 4.2. The details are described below.

(1) Selection of experts

It is worthwhile to involve multiple experts and aggregate their opinions of probability assessment. Ferrell(1985) suggest that three to five experts are a good number. Three experts, one water manager Mr. Mingyuan Fan and two researchers Ms. Huawei Chen and Dr. Jian Liu, from the Water Resource Research Institute in Shangdong Province were involved and consulted for predicting water demand. Mr. Fan works on water resources management, and especially focuses on optimal water resources distribution in the YRD. Ms. Chen and Dr. Liu work on hydrology and water resource management. They have been working and researching about water resources issues in the Yellow River Delta for years and have experience in modelling water availability and demand, planning water infrastructure and allocating water in the YRD. In the study, experts are identified without using calibration approaches, and they are assumed to be equally qualified for the probability assessment.

(2) 'Training' of experts

As the experts already have plenty of knowledge and experience about water resources planning and management in the Yellow River Delta, the training mainly aims to help them to get familiar with the knowledge of probability, in order to build their comfort with the elicitation process. To explain the 50% quartile of a variable, denoted as X (50%), questions were asked such as "which value of X do you think is equally likely to be exceeded or not". To elicit the 25% quartile, questions were asked such as "what is the value of X located in the middle between the X (50%) and the lowest possible value of X?" Another training task is to help them get familiar with the SHELF procedure and software. The SHELF package includes the procedure and notes, and they were explained to experts. To practice the SHELF-Quartile elicitation process, the probability distribution of the historical annual urban population growth rate in the YRD was estimated by them. Their elicited probability distributions were compared with the probability distribution from the observed data (although very few). Through this exercise, the experts were expected to have better understanding of probability distributions and the elicitation approach.

(3) Elicitation process using SHELF

Although the experts already have plenty of knowledge and experience about water resources planning and management in the YRD, available materials about the quantities of interest were sent beforehand. More information is helpful to avoid “availability heuristic” in which experts rely only on the knowledge already in their mind.

Before the elicitation process, the purpose of the elicitation and the uncertainties should be explained explicitly. The variables were defined as explained in section 5.5.4. The quartile method was chosen for probability elicitation. In practice, it is not possible to estimate the probability distribution directly, but rather the quartiles or moments of the probability distribution. The upper and lowers bounds, as well as 25%, 50%, and 75% quartiles, were elicited in order to characterize the tails, the position, and the quartiles in between, which helps to decide the shape and fit the curve with an appropriate probability distribution. The experts were consulted and had to make judgement separately for each variable. With the judgement of quartiles, a probability distribution can be fit using SHELF software, and the expert can adjust and correct the distribution through the visualized curve.

Appendix B. Quartile estimation for annual growth rate of water demand variables in the next 30 years from three experts under SHELF procedure. Unit (%)

Quartile	Index	Variable	Description	*E 1*	*E2*	*E3*	Index	Variable	Description	*E 1*	*E2*	*E 3*
0				0.5	0.5	0.5				0.5	0.5	0.5
0.25				2	1	2				0.8	0.6	0.55
0.5	1	*r.pop1*	urban population	3.00	2	2.5	11	*r.area1*	paddy rice area	1.00	0.7	0.7
0.75				3.20	3	3				1.20	1	1
1				3.50	3.5	3.5				1.30	1.3	1.3
0				-3	-3	-3				0.5	0.51	0.51
0.25				-2.5	-2.5	-1.5				2	0.7	0.55
0.5	2	*r.pop2*	rural population	-2	-1.5	-1.3	12	*r.area2*	other crop area	2.5	1.5	1
0.75				-1.5	0.5	-0.2				2.6	2.5	2.5
1				2	2	2				3	3	3
0				-2.5	-2.5	-2.5				0.5	0.48	0.48
0.25				-0.4	-0.5	-0.1				1	0.8	0.55
0.5	3	*r.Ipop1*	urban water use intensity	0.15	0.1	0.1	13	*r.area3*	vegetable area	1.2	1	0.7
0.75				0.16	0.15	0.15				1.5	1.5	1.4
1				0.17	0.17	0.17				2	2	2
0				-8.7	-8.7	-8.7				1	1	1
0.25				0.5	-7	-0.5				5	2	1.5
0.5	4	*r.Ipop2*	rural water use intensity	0.8	-5	0.1	14	*r.area4*	orchard area	6	3	2
0.75				0.9	-3	0.15				6.8	5	2.7
1				1	1	1				7	7	7
0				-3	-3	-3				-1.8	-1.8	-1.8
0.25				5	2	8				-0.5	-1	-0.5
0.5	5	*r.prd1*	industry production	7	6	8.5	15	*r.area5*	grass area	1	0.5	0.7
0.75				9	8	9				1.2	1	1
1				10	10	10				2	2	2
0				-4	-4	-4				-1.1	-1.1	-1.1
0.25				5	1	7				-0.5	-0.8	-1
0.5	6	*r.prd2*	archetect production	6	4	7.1	16	*r.area6*	fishing area	0	0.2	0.5
0.75				6.5	6	7.4				0.3	0.5	0.8
1				7.5	7.5	7.5				1	1	1
0				5	5	5				-2	-2	-2
0.25				8	7	5.5				-1.8	-1.5	-1.75
0.5	7	*r.prd3*	tertiary production	15	10	6.5	17	*r.Iagr1*	paddy rice irrgation intensity	-1	-1	-1.7
0.75				18	15	7				-0.5	-0.6	-1.5
1				20	20	20				0	0	0
0				-5	-5	-5				-5	-5	-5
0.25				-4.5	-4.5	-4.5				0	-4	-4
0.5	8	*r.Iind1*	industry water use intensity	-4	-4	-3.5	18	*r.Iagr2*	other crop irrgation intensity	2.2	-3	-3
0.75				-3	-2	-3				2.5	1	-2
1				1	1	1				3	3	3
0				-2	-2	-2				-5	-5	-5
0.25				-1.9	-1.5	-1.5				0	-4.5	-4.5
0.5	9	*r.Iind2*	archetect water use intensity	-1.8	-1	-1.3	19	*r.Iagr3*	vegetable irrgation intensity	2.3	-4	-2.5
0.75				-1	0.34	-1				2.5	-2	-2
1				2	2	2				3	3	3
0				-10	-10	-10						
0.25				-9	-7.5	-8						
0.5	10	*r.Iind3*	tertiary water use intensity	-8	-5	-6.5						
0.75				-6	-3	-4.5						
1				-1	-1	-1						

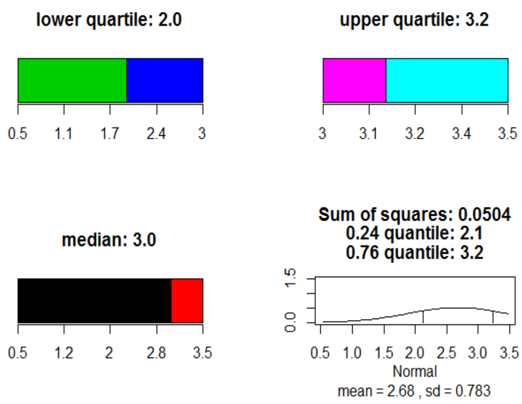
Appendix C Probability fitting of urban population growth rate using SHELF Quartile method

Quartile estimation of urban population growth rate by three experts

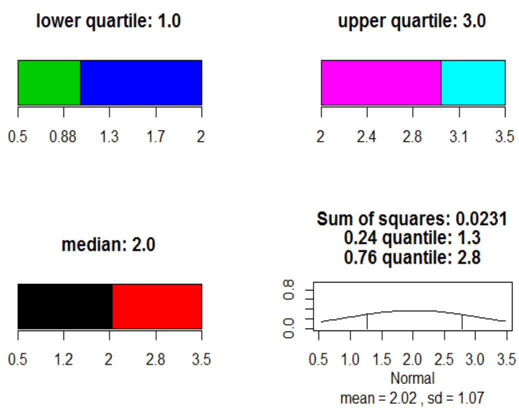
Quartile	Index	Variable	Description	*E 1*	*E2*	*E3*
0				0.5	0.5	0.5
0.25				2	1	2
0.5	1	*r.pop1*	urban population	3.00	2	2.5
0.75				3.20	3	3
1				3.50	3.5	3.5

Figures of distribution fit for *r.pop1* with SHELF

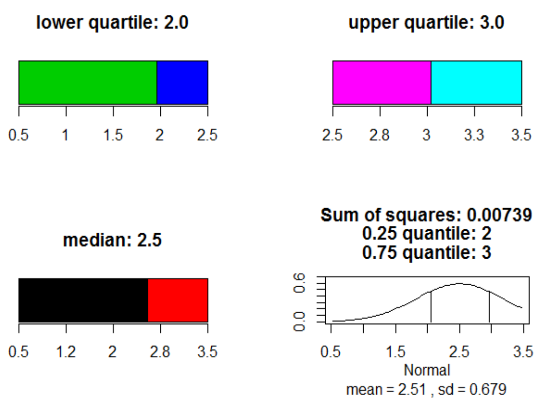
(E1)



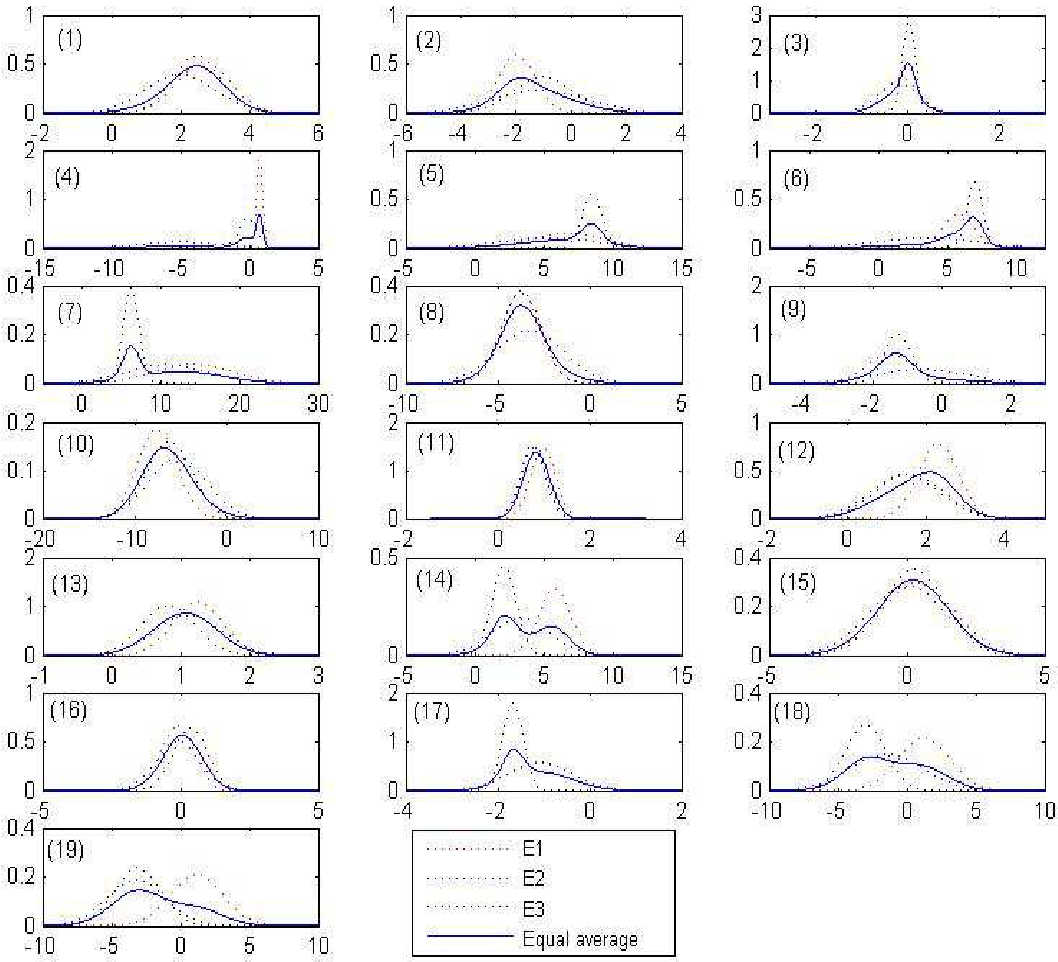
(E2)



(E3)



Appendix D Prior probability distributions fitted with SHELF and resulting combined probability distributions using an equally weighted average approach



Appendix E Correlation matrix (Product moment correlation) among variables

(1) Pearson's correlation of variables to model domestic water demand

	r.pop1	*r.pop2*	*r.Idom1*	*r.Idom2*
r.pop1	1	-0.8	-0.45	0
r.pop2	-0.8	1	0	-0.25
r.Idom1	-0.45	0	1	0
r.Idom2	0	-0.25	0	1

(2) Pearson's correlation of variables to model industrial water demand

	r.prd1	*r.prd2*	*r.prd3*	*r.Iind1*	*r.Iind2*	*r.Iind3*
r.prd1	1	0.50	0.45	-0.6	-0.2	-0.25
r.prd2	0.50	1	0.40	-0.2	-0.6	-0.2
r.prd3	0.45	0.40	1	-0.4	-0.4	-0.6
r.Iind1	-0.6	-0.2	-0.4	1	0	0
r.Iind2	-0.2	-0.6	-0.4	0	1	0
r.Iind3	-0.25	-0.2	-0.6	0	0	1

(3) Pearson's correlation of variables to model agricultural water demand

	r.area1	*r.area2*	*r.area3*	*r.area4*	*r.area5*	*r.area6*	*r.Iarea1*	*r.Iarea2*	*r.Iarea3*
r.area1	1	0.6	0.45	0.45	0.3	0.2	-0.6	-0.25	-0.25
r.area2	0.6	1	0.5	0.5	0.35	0.25	-0.3	-0.6	-0.3
r.area3	0.45	0.5	1	0.4	0.3	0.2	-0.2	-0.2	-0.6
r.area4	0.45	0.5	0.4	1	0.25	0.15	-0.15	-0.15	-0.15
r.area5	0.3	0.35	0.3	0.25	1	0.1	-0.1	-0.1	-0.1
r.area6	0.2	0.25	0.2	0.15	0.1	1	-0.1	-0.1	-0.1
r.Iarea1	-0.6	-0.3	-0.2	-0.15	-0.1	-0.1	1	0	0
r.Iarea2	-0.25	-0.6	-0.2	-0.15	-0.1	-0.1	0	1	0
r.Iarea3	-0.25	-0.3	-0.6	-0.15	-0.1	-0.1	0	0	1

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About the author

Congli Dong was born in Hengyang City, Hunan Province, China, on July 25, 1986. In 2007, she got her Bachelor degree from Hohai Unversity, Nanjing, China. In 2009, she received her Master degree on Hydrology and Water Resource Engineering in Hohai University. The title of her Master thesis is “Modelling agricultural non-point source pollution using AnnAGNPS model in Chishan Lake, China.” In the same year, she started her PhD in the Department of Water Resources Management at Delft University of Technology. In 2012, she visited research institutions-the Chinese Academy of Sciences (CAS), Beijing, and Water Research Institution, Shandong, China. During her PhD, she attended courses and training on Climate Science and Entrepreneurship from Climate-KIC, the EU's main climate innovation initiative. She will receive the Climate-KIC PhD Label in Innovation Festival in Valencia, Spain, 2014.

Scientific publications

- "Scenario-based Expert Elicitation Approach for Future Water Demand Projection in the Yellow River Delta, China", C. Dong, G., Schoups, N. van de Giesen, 2014, under review.
- "Probabilistic scenario development to analyse future runoff in the Yellow River Basin", C. Dong, G., Schoups, N. van de Giesen, Environmental Engineering and Management Journal, 2013.
- "Scenario development for water resource planning and management: A review", C. Dong, G., Schoups, N. van de Giesen, Technological Forecasting & Social Change, 2012.
- "Characterizing uncertainty of hydro-climatic variables for water management in the Yellow River Basin: Learning from the past", C. Dong, G., Schoups, N. van de Giesen, the 5th International Yellow River Forum, Zhengzhou, China, 2012.
- "Scenario Development for Decision-Making in Water Resources Planning and Management", C. Dong, N. van de Giesen, International Symposium on Water resource and Environmental Protection (ISWERP), Xian, China, 2011.
- "The Parameters Sensitivity Analysis of AnnAGNPs Non-point Pollution Model", C. Dong, Z.C. Dong, X.B, Qin, China Science paper online, 2009.
- "Study of a dynamic model for making an effect evaluation of Yangtze River-Taihu Lake water transfer", D.Y. Li, Z.C. Dong, C. Dong, Proceedings of First International Conference of Modelling and Simulation, 2008 International Pre-Olympic Congress on Computer Science. Nanjing, China, August 4-7, 2008.

Poster and Oral Presentations

- "Probabilistic scenario-based decision making for water resource planning and management", C. Dong, G. Schoups, N. van de Giesen, Changjiang Water Resource Commission Workshop, Delft University of Technology, 2014. (Oral presentation)
- "Estimate the impact of climate change on future water availability in the Yellow River Basin, China" , C. Dong, G. Schoups, N. van de Giesen, Boussinesq lecture, Amsterdam, 2013. (Oral presentation)

- “Scenario-based decision making in water resource planning and management: a case study in the Yellow River Delta, China”, C. Dong, G., Schoups, N. van de Giesen, Geophysical Research Abstracts, Vol. 15, EGU2013-3058-1, 2013.
- “Probabilistic scenario development to analyze future runoff in the Yellow River Basin”, C. Dong, G. Schoups, N. van de Giesen, International Symposium on Recent Advances in Water Resources Management & Pollution Control- with Special Focus on China (ICAERE), Galway, Ireland, 2012.
- “Probabilistic Scenario-based Approach to Analyze Future Runoff in the Yellow River Basin under Climate Change”, C. Dong, G. Schoups, N. van de Giesen, World Congress on Water, Climate and Energy, Dublin, Ireland, 2012. (Oral Presentation)
- “Probabilistic scenario-based water resource planning and management: A case study in the Yellow River Basin, China”, C. Dong, G., Schoups, N. van de Giesen, Geophysical Research Abstracts, Vol. 14, EGU2012-3522, 2012. (Oral Presentation)
- “Scenario-development to analyze future fresh water availability in the Yellow River Delta”, C. Dong, N. van de Giesen, Geophysical Research Abstracts, Vol. 12, EGU 2010-1563, 2010.