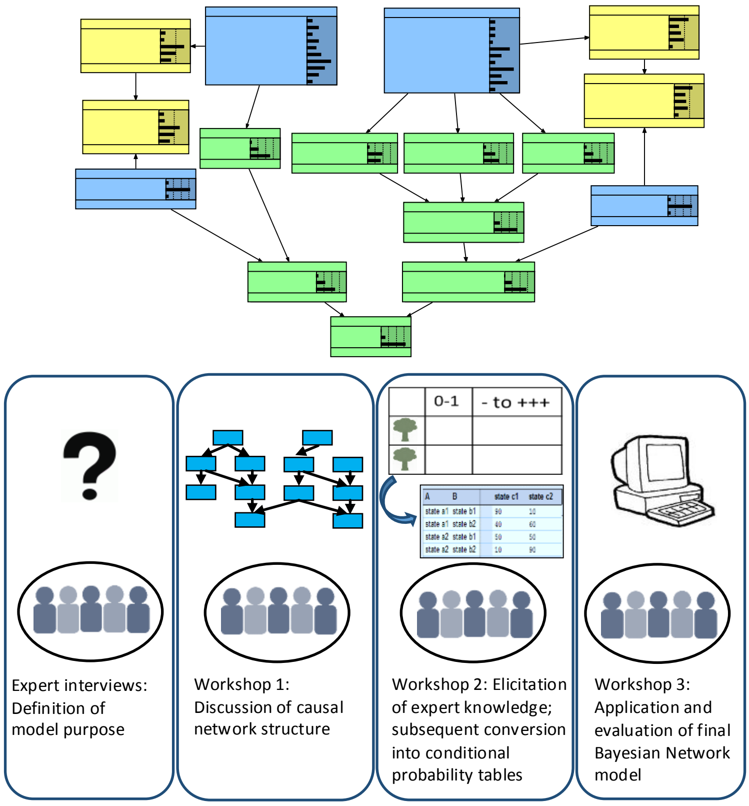
11

Expert-based Bayesian Network modeling for environmental management



Bayesian Network modeling with experts

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Expert-based Bayesian Network modeling for environmental management

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Abstract

Bayesian Networks are computer-based environmental models that are frequently used to support decision-making under uncertainty. Under data scarce conditions, Bayesian Networks can be developed, parameterized, and run based on expert knowledge only. However, the efficiency of expert-based Bayesian Network modeling is limited by the difficulty in deriving model inputs in the time available during expert workshops. This thesis therefore aimed at developing a simple and robust method for deriving conditional probability tables from expert estimates in a time-efficient way. The design and application of this new elicitation and conversion method is demonstrated using a case study in Xinjiang, Northwest China. The key characteristics of this method are its time-efficiency and the approach to use different conversion tables based on varying levels of confidence. Although the method has its limitations, e.g. it can only be applied for variables with one conditioning variable; it provides the opportunity to support the parameterization of Bayesian Networks which would otherwise remain half-finished due to time constraints. In addition, a case study in the Murray-Darling Basin, Australia, is used to compare Bayesian Network types and software to improve the presentation clarity of large Bayesian Networks. Both case studies aimed at gaining insights on how to improve the applicability of Bayesian Networks to support environmental management.

Summary

Introduction. Environmental problems are complex. Due to diverse interrelations and interdependencies between nature and society, it is difficult to anticipate or predict all natural responses to anthropogenic influences and vice versa. Computer-based environmental models constitute a means to assist environmental managers to make more informed decisions under uncertainty. An environmental model is a simplified representation of a real-world system which can either be used for diagnostic or predictive purposes. For example, models can be used to ascertain causes for observed environmental pollution or to assess the expected outcome of various management alternatives.

Many problems at the nature-society interface are insufficiently covered by empirical data. Modeling tools which incorporate various input data types are therefore needed to use and combine the best data available. This can be done through Bayesian Network models, which can utilize outputs from other models, data derived from statistics, measurements, scientific literature or household surveys, as well as expert knowledge. Under data scarce conditions, Bayesian Networks can even be developed, parameterized, and run based on expert knowledge only.

Involving local experts and stakeholders from various disciplines and fields is a cost and time efficient way of obtaining information. In addition, it helps to better understand complex problems, to develop better informed models under data scarcity and to jointly find holistic solutions to real-world problems. More importantly, it has a significant impact on the likelihood that model outcomes are put into use after the completion of the modeling process.

The efficiency of using expert-based Bayesian Network modeling is limited by the difficulty in deriving model inputs in the time available during expert workshops. Many people are not familiar with probabilistic thinking and are not used to formulate their knowledge in the form of probabilities. As Bayesian Networks are probabilistic causal models, the parameters are expressed in conditional probability values. The “conditional probability” of an event is the likelihood that an event occurs given another event has already happened. To fill so-called conditional probability tables, an expert needs to answer many “if-then-questions”. For example, “if event A has already happened, then event B will occur with a probability of __%“. In addition to this unusual format, these conditional probability tables grow exponentially with the number of conditioning variables. Filling these tables manually is very time-consuming and cognitively challenging for experts and stakeholders.

This thesis aims at developing a simple and robust method for deriving conditional probability tables from expert estimates, which is demonstrated using a case study in Northwest China. As the modeling process in the case study region had to be conducted in three 3-hour-workshops, it was predestined for testing "expert-friendly" elicitation formats that can be used under serious time constraints. In addition, a case study in Australia provided the opportunity to compare Bayesian Network types and software to improve the presentation clarity of large Bayesian Networks.

Bayesian Networks. A Bayesian Network is a probabilistic causal model of a selected real system. The system's components and the relationships between them are represented in the form of a causal network. In a Bayesian Network, a link between two variables indicates that one variable is conditionally dependent on the other. The strength of this dependence is expressed in conditional probabilities. Among other rules of probability theory, the Bayesian Network software applies the *Bayes' rule* which was derived by the 18^{th}-century mathematician Reverend Thomas Bayes.

Bayesian Network models emerged from Artificial Intelligence research and were first applied in the fields of medicine and automated fault diagnosis. Since the late-1990s, Bayesian Networks are increasingly being used in support of environmental management. Among other reasons, as they offer the possibility to utilize and combine a wide range of input data types and to integrate experts' knowledge within participatory modeling processes.

Expert-based Bayesian Network modeling. Experts can be involved at various stages of a Bayesian Network modeling process. For example, experts can identify variables and link them into a causal network, they can estimate conditional probability values, or finally apply and evaluate the model. In absence of other data sources, the quality of expert-based Bayesian Networks hinges on the selection of experts, their willingness to invest time in the process, and the design of consultation process and elicitation procedure.

A literature review revealed that in most expert-based Bayesian Network applications experts were required to estimate probability values – either with empty (conditional) probability tables or with the help of probability scales. Only in few applications, estimates were elicited as weights, as frequencies, as rankings or in other formats. The existing elicitation formats were inadequate for the case study in Northwest China. As the whole elicitation needed to be completed within one hour, the elicitation categories needed to be more intuitive and easy to understand. The case study therefore had the methodological purpose to develop a simple and even more time-efficient elicitation method to be used in a workshop setting.

Case study Northwest China. This case study was conducted in oasis towns of the Tarim Basin in Xinjiang Uighur Autonomous Region, Northwest China. It was designed as a three-year study in the frame of the SuMaRiO project (Sustainable Management of River Oasis along the Tarim River, China). One of SuMaRiO's main objectives is to develop methods to assess ecosystem services and to support the integration of the ecosystem services concept into land and water management in the water-scarce Tarim Basin. In general, ecosystem services are defined as benefits that people obtain from ecosystems. The idea behind integrating this concept into land and water management is to draw attention to the plentitude of services provided by healthy ecosystems – instead of only focusing on irrigated agricultural products, such as cotton. In line with the goals of the SuMaRiO project, this case study aimed at developing, applying, and evaluating participatory modeling methods to support sustainable environmental management in the case study region.

Urban and peri-urban vegetation provides many ecosystem services for people living in oasis towns at the margin of the Taklamakan desert. As towns in Southern Xinjiang, such as Aksu and Korla, are exposed to dust weather approximately 100 days per year, dust weather mitigation is one of the most relevant ecosystem services in the region. The term dust weather describes dust events in which desert dust particles are raised and transported by the wind. The provision of shade is another ecosystem service in these oasis towns, which experience temperatures that reach 40°C or higher during summer months. Under the impact of climate change, it is most likely that the arid region of the Taklamakan desert would experience even higher temperatures.

The Bayesian Network therefore compares plant species in their ability to mitigate dust weather and to provide shade as well as their resulting irrigation needs. The methodological challenge of this case study was to develop a Bayesian Network under data scarcity and with few chances to meet local experts – and only for a short time. In the course of a workshop series, local experts from urban landscape planning and forestry management as well as local researchers from various disciplines jointly developed two Bayesian Networks which were later merged into one network.

During the first workshop, a preliminary network structure was discussed and improved. During the second workshop, expert estimates as well as their confidence in these estimates were elicited in the form of ratings on a scale of – to +++ and numerical values (0-1). In the following step, four conversion tables were designed to systematically transform these estimates into conditional probability values according to different levels of confidence. During the third workshop, the fully parameterized model was applied and evaluated by the workshop participants.

This case study resulted in a fully functioning Bayesian Network which can be used to compare 11 peri-urban plant species in their ability to mitigate dust weather and 10 urban plant species in their ability to provide shade as well as their irrigation needs. The final model exactly addresses the knowledge gap expressed by local urban landscape planners during an expert interview prior to the modeling process.

Case study Australia. This case study is the result of a three-month research stay in Australia. The task was to identify the broad range of ecosystem services provided by ten wetland sites in the Murray-Darling Basin, and to develop a Bayesian Network that shows the links between environmental flows, the ecosystem condition and ecosystem services. Environmental flows are water flows necessary to sustain freshwater ecosystems and to secure the services for human well-being provided by them. In contrast to the workshop series of the Northwest China case study, this Bayesian Network was solely developed in cooperation with an ecological modeler. The conditional probability tables were filled based on expert knowledge, so-called ecological character descriptions, and equations.

The methodological motivation behind this particular study was to exhaust the potential of Bayesian Networks to model multiple ecosystem services simultaneously, which has not been explored by previous Bayesian Network applications. In addition, the size of the final model provided the opportunity to compare different Bayesian Network types with regard to "user-friendliness". This comparison showed that there is a trade-off between presentation clarity and accurate visualization of causal relationships.

This case study resulted in a fully functioning Bayesian Network model which can be used to analyze the impact of annual water supply on the ecosystem condition of ten wetlands and all their ecosystem services simultaneously. For example, it shows how environmental flows can help to sustain a healthy ecosystem condition and to provide ecosystem services in case of low water availability.

Conclusion. Whilst the case studies conducted in Northwest China and Australia differ in time spent, depth of study, and findings, they share a common ground in methodology and on the subject level. Both case studies aimed at gaining insights on how to improve the applicability of Bayesian Networks to support environmental management.

The scientific contribution of this thesis consists of the design and application of an elicitation and conversion method that complements existing techniques. The key characteristics of this method are its time-efficiency and the approach to use different conversion tables based on varying levels of confidence. Although this method has its limitations, e.g. it can only be applied for variables with one conditioning variable; it provides the opportunity to support the parameterization of Bayesian Networks which would otherwise remain half-finished due to time constraints. This thesis also broaches the issue of presentation clarity of large Bayesian Networks and nested Bayesian Networks. The short comparison neither advocates a Bayesian Network type nor software; it rather highlights the need to consider the applicability and user-friendliness of large models.

The real-world purpose of the case study in Northwest China was to support and inform local vegetation managers and planners. It is difficult to assess the contribution of this case study for local environmental management. The research conditions in Northwest China made it impossible to invite the same group of local experts to all workshops. The high fluctuations of workshop participants reduced the perceived “ownership” of the modeling process and model results. Nevertheless, each workshop provided a platform for discussion and mutual learning. As in many other participatory Bayesian Network applications, the knowledge exchange during the modeling process was at least as valuable to the workshop participants as model results.

Zusammenfassung

Einleitung. Umweltprobleme sind komplex. Die vielfältigen Wechselbeziehungen und gegenseitigen Abhängigkeiten zwischen Natur und Gesellschaft erschweren die Aufgabe, Reaktionen der Natur auf anthropogene Einflüsse zu erahnen oder vorherzusagen. Computerbasierte Umweltmodelle können Umweltmanager darin unterstütztzen, in dieser Ungewissheit informiertere Entscheidungen zu treffen. Ein Umweltmodell ist eine vereinfachte Darstellung eines real existierenden Systems, das zur Diagnose oder zur Voraussage verwendet werden kann. Zum Beispiel um die Ursachen von beobachteten Umweltverschmutzungen zu ermitteln oder die zu erwartenden Folgen verschiedener Managementmaßnahmen zu beurteilen.

Zu vielen Mensch-Umwelt-Problemen liegen nur wenige empirische Daten vor. Um vorhandene Daten optimal nutzen und kombinieren zu können, sind Modellierungstools notwendig, die unterschiedlichste Inputdaten verwenden können. Dieses Kriterium wird von Bayes'schen Netzen erfüllt, da sie Ergebnisse anderer Modelle, statistische Daten, Messwerte, Erkenntnisse aus wissenschaftlichen Veröffentlichungen, Haushaltbefragungen sowie Expertenwissen verarbeiten können. Falls die Datenknappheit es notwendig macht, können Bayes'sche Netze auch ausschließlich mit Expertenwissen entwickelt, parametrisiert und angewendet werden.

Lokale Experten und Stakeholder aus unterschiedlichen Disziplinen und Arbeitsfeldern in die Modellierung einzubeziehen ist eine kosten- und zeiteffiziente Methode, um Informationen zu erhalten. Zudem hilft dies, komplexe Probleme besser zu verstehen, informiertere Modelle unter Datenknappheit zu entwickeln und gemeinsam ganzheitliche Lösungsansätze für real existierende Probleme zu finden. Die Einbindung verschiedener Akteure erhöht auch die Wahrscheinlichkeit, dass Modellergebnisse nach Beendigung des Forschungsprojektes angewendet werden.

Die experten-basierte Modellierung mit Bayes'schen Netzen wird dadurch erschwert, dass die Erhebung von Inputdaten meist mehr Zeit benötigt als im Rahmen von Experten-Workshops zur Verfügung steht. Viele Menschen sind es nicht gewohnt ihr Wissen in Form von Wahrscheinlichkeiten wiederzugeben. Da Bayes'sche Netze probabilistische kausale Modelle sind, werden ihre Parameter jedoch in bedingten Wahrscheinlichkeiten ausgedrückt. Die "bedingte Wahrscheinlichkeit" eines Ereignisses ist die Wahrscheinlichkeit dass das Ereignis stattfindet, gegeben dem Fall, dass ein anderes Ereignis bereits stattgefunden hat. Um sogenannte bedingte Wahrscheinlichkeitstabellen auszufüllen, muss ein Experte viele „wenn-dann-Fragen" beantworten: „Wenn Ereignis A bereits

eingetroffen ist, wie hoch ist dann die Wahrscheinlichkeit, dass Ereignis B eintrifft?“. Zusätzlich zu diesem ungewöhnlichen Format, vergrößern sich diese bedingten Wahrscheinlichkeitstabellen exponentiell mit der Zahl der Variablen, welche die Eintrittswahrscheinlichkeit eines Ereignisses beeinflussen. Solche Tabellen per Hand auszufüllen stellt für Experten eine zeitaufwändige und kognitiv herausfordernde Aufgabe dar.

In dieser Arbeit wird, im Rahmen einer Fallstudie in Nordwestchina, eine einfache und robuste Methode entwickelt, um Expertenschätzungen in bedingte Wahrscheinlichkeitstabellen umzuwandeln. Da der Modellierungsprozess im Rahmen dreier drei-stündiger Expertenworkshops durchgeführt werden musste, war diese Fallstudie prädestiniert dafür, „expertenfreundliche“ Erhebungsmethoden zu testen, die unter starkem Zeitdruck angewendet werden können. Zusätzlich bot eine Fallstudie in Australien die Möglichkeit, verschiedene Arten von Bayes’schen Netzen und Software für deren Erstellung zu vergleichen, um die Übersichtlichkeit großer Bayes’scher Netze zu verbessern.

Bayes’sche Netze. Ein Bayes’sches Netz ist ein probabilistisches, kausales Modell eines ausgewählten real existierenden Systems. Die Komponenten des Systems und die Zusammenhänge zwischen ihnen werden in Form eines kausalen Netzes dargestellt. In einem Bayes’schen Netz zeigt ein Pfeil zwischen zwei Variablen an, dass die eine Variable von der anderen beeinflusst bzw. bedingt wird. Die Stärke dieser Abhängigkeit wird in bedingten Wahrscheinlichkeiten ausgedrückt. Der *Satz von Bayes*, welcher im 18. Jahrhundert vom Pfarrer und Mathematiker Thomas Bayes entwickelt worden ist, wird neben anderen Regeln der Wahrscheinlichkeitstheorie für die Modellierung mit Bayes’schen Netzen verwendet.

Bayes’sche Netze stammen aus dem Bereich der Erforschung Künstlicher Intelligenz und wurden zunächst im Bereich der Medizin und der automatischen Fehlerdiagnose verwendet. Seit den späten 1990er Jahren werden Bayes’sche Netze vermehrt zur Unterstützung im Umweltmanagement verwendet. Unter anderem bietet diese Methode die Möglichkeit, eine Vielzahl von Inputdatentypen zu nutzen und zu kombinieren, sowie im Rahmen von partitzipativen Modellierungsprozessen Expertenwissen zu erheben und zu integrieren.

Experten-basierte Modellierung mit Bayes’schen Netzen. Experten können in mehrere Schritte eines Modellierungsprozesses eingebunden werden. Zum Beispiel um Variablen zu identifizieren, sie zu einem kausalen Netz zu verbinden, um bedingte Wahrscheinlichkeiten zu schätzen, oder um das Modell anzuwenden und zu evaluieren. Wenn keine anderen Daten verwendet werden können, hängt die Qualität eines Experten-basierten Bayes’schen Netzes von der Auswahl der

Experten, ihrer Bereitschaft, Zeit in den Modellierungsprozess zu investieren und von der Gestaltung der Expertenerhebung ab.

Eine Literaturstudie hat ergeben, dass in den meisten Anwendungen Experten-basierter Bayes'scher Netze die Experten aufgefordert wurden, bedingte Wahrscheinlichkeiten zu schätzen – entweder mit leeren (bedingten) Wahrscheinlichkeitstabellen oder mit Wahrscheinlichkeitsskalen. Nur in wenigen Anwendungen wurden Schätzungen in Form von Gewichtungen, Häufigkeiten, Rangfolgen oder anderen Formaten erhoben. Die bestehenden Erhebungsformate konnten in der Fallstudie in Nordwestchina nicht angewendet werden. Da die gesamte Erhebung nur eine Stunde dauern durfte, mussten die Erhebungskategorien intuitiver und einfacher zu verstehen sein. Daher hatte diese Fallstudie den methodologischen Anspruch, eine einfache und zeit-effizientere Erhebungsmethode zu entwickeln, die in Rahmen von Expertenworkshops angewendet werden kann.

Fallstudie Nordwestchina. Diese Fallstudie wurde in Oasenstädten des Tarimbeckens im Uigurischen Autonomen Gebiet Xinjiang in Nordwestchina durchgeführt. Sie wurde innerhalb von drei Jahren im Rahmen des SuMaRiO-Projektes (<u>Su</u>stainable <u>Ma</u>nagement of <u>Ri</u>ver <u>O</u>asis along the Tarim River, China) abgeschlossen. Hauptziele des SuMaRiO-Projektes sind es, Methoden zu entwickeln, mit denen Ökosystemdienstleistungen erfasst werden können, sowie die Integration des Konzepts der Ökosystemdienstleistungen in Land- und Wassermanagement im wasserarmen Tarimbecken zu unterstützen. „Ökosystemdienstleistungen" sind die Vorteile oder Dienstleistungen, die Menschen von intakten Ökosystemen beziehen. Dieses Konzept im Land- und Wassermanagement einzubringen soll die Aufmerksamkeit darauf lenken, dass Menschen auf vielseitige Weise von intakten Ökosystemen profitieren können – nicht nur von dem Anbau wasserintensiver Agrarprodukte, wie zum Beispiel Baumwolle. In Übereinstimmung mit den SuMaRiO-Zielen diente diese Fallstudie dazu, partizipative Modellierungsmethoden zu entwickeln, anzuwenden und zu evaluieren, um ein nachhaltiges Umweltmanagement in der Region zu unterstützen.

Die Menschen, die in Oasenstädten am Rande der Taklamakan-Wüste leben, profitieren von vielen Ökosystemdienstleistungen, welche die urbane und peri-urbane Vegetation für sie bereitstellt. Da Städte im Süden Xinjiangs an etwa 100 Tagen im Jahr von Staubwetter betroffen sind, ist die Verminderung von Staubwetter eine der wichtigsten Ökosystemdienstleistungen in der Region. Der Begriff „Staubwetter" beschreibt den Zustand wenn (Wüsten-) Staubpartikel aufgewirbelt und vom Wind transportiert wird. Die Bereitstellung von Schatten ist eine weitere Ökosystemdienstleistung, da in den Oasenstädten während des

Sommers Temperaturen von 40°C und höher herrschen. Unter dem Einfluss des Klimawandels wird diese aride Wüstenregion höchstwahrscheinlich noch höhere Temperaturen erfahren. Das Bayes'sche Netz vergleicht daher Pflanzenarten in ihrer Fähigkeit, Staubwetter zu vermindern und Schatten zu spenden sowie den resultierenden Bewässerungsbedarf.

Die methodologische Herausforderung dieser Fallstudie war es ein Bayes'sches Netz zu entwickeln – trotz der Datenknappheit und obwohl Experten nur selten und auch nur für kurze Zeit konsultiert werden konnten. In Rahmen einer Workshopreihe haben lokale Experten aus den Bereichen der Urbanen Landschaftsplanung und dem Waldmanagement gemeinsam zwei Bayes'sche Netze entwickelt die anschließend zu einem Netz zusammengefügt wurden.

Während des ersten Workshops wurde die vorläufige Struktur des Netzes diskutiert und verbessert. Während des zweiten Workshops wurden sowohl Experteneinschätzungen in Form von Bewertungen auf einer Skala von – bis +++ und in numerischen Werten (0-1) als auch ihre Zuversicht in die Richtigkeit ihrer Einschätzungen erhoben. Anschließend wurden vier Konversionstabellen erstellt, mit denen – unter Einbeziehung des Zuversichtsgrades – die erhobenen Werte in bedingte Wahrscheinlichkeitsverteilungen umgewandelt werden konnten. Während des dritten Workshops wurde das vollständig parametrisierte Modell von den Workshopteilnehmern verwendet und evaluiert.

Das Ergebnis dieser Fallstudie ist ein voll funktionstüchtiges Bayes'sches Netz welches peri-urbane und urbane Pflanzenarten gegenüberstellt. Es vergleicht die Fähigkeit 11 peri-urbaner Pflanzenarten, Staubwetter zu vermindern, die Fähigkeit 10 urbaner Pflanzenarten, Schatten zu spenden sowie ihren Bewässerungsbedarf. Es schließt damit die Wissenslücke, die während eines Experteninterviews mit Grünflächenplanern vor Beginn des Prozesses genannt wurde.

Fallstudie Australien. Diese Fallstudie ist das Ergebnis eines dreimonatigen Forschungsaufenthaltes in Australien. Zunächst galt es die Vielzahl der Ökosystemdienstleistungen zu identifizieren, die von Feuchtgebieten im Murray-Darling-Becken bereitgestellt werden. Dann sollte ein Bayes'sches Netz erstellt werden, um die Zusammenhänge zwischen sogenannten *environmental flows*, dem Zustand von Ökosystemen und Ökosystemdienstleistungen aufzuzeigen. „Environmental flows" sind Wasserströme bzw. Wassermengen, die notwendig sind, um Süßwasserökosysteme zu erhalten und damit auch ihre Dienstleistungen zu sichern, die zum menschlichen Wohlergehen beitragen. Im Gegensatz zu der Fallstudie in Nordwestchina wurde dieses Bayes'sches Netz nur in Kooperation mit einer ökologischen Modelliererin erstellt. Die bedingten Wahrscheinlichkeitstabellen wurden basierend auf ihrem Expertenwissen, Informationen zu den ökologischen Eigenschaften der Feuchtgebiete („*ecological character descriptions*"), und Gleichungen erstellt.

Die methodologische Motivation hinter dieser Fallstudie war es, mit Bayes'schen Netzen eine Vielzahl von Ökosystemdienstleitungen gleichzeitig zu modellieren, da bisherige Anwendungen sich bisher auf 1-2 Ökosystemdienstleistungen beschränkt hatten. Zudem bot die Größe des Bayes'schen Netzes die Möglichkeit, verschiedene Arten von Bayes'schen Netzen auf ihre Benutzerfreundlichkeit zu prüfen. Der Vergleich zeigt dass es einen Zielkonflikt gibt zwischen der Übersichtlichkeit eines Modells und einer verständlichen Darstellung kausaler Zusammenhänge.

Diese Fallstudie resultierte in einem funktionierenden Bayes'schen Netz welches dafür genutzt werden kann, den Einfluss des jährlichen Wasserhaushalts auf den Ökosystemzustand von zehn Feuchtgebieten und ihre Ökosystemdienstleistungen gleichzeitig darzustellen. Es zeigt zum Beispiel, wie das Bereitstellen von zusätzlichen Wassermengen für die Ökosysteme („*environmental flows*") dabei helfen kann, Ökosysteme intakt zu halten und ihre Ökosystemdienstleistungen auch in Jahren mit geringerer Wasserverfügbarkeit zu sichern.

Schlussfolgerung. Obwohl die Fallstudien sich in Projektdauer, Studientiefe, und Erkenntnissen unterscheiden, teilen sie die gleiche Methodologie und befassen sich mit ähnlichen Inhalten. Beide Fallstudien zielten darauf ab, Erkenntnisse zu gewinnen, um die Anwendbarkeit von Bayes'schen Netzen im Bereich des Umweltmanagements zu verbessern.

Der wissenschaftliche Beitrag dieser Arbeit besteht aus der Erstellung und der Anwendung einer Erhebungs- und Konversionsmethode, die bisherige Herangehensweisen zur Ableitung von bedingten Wahrscheinlichkeiten ergänzt. Die Merkmale dieser Methode sind ihre Zeitersparnis und der Ansatz, die Zuversicht der Experten bei der Konversion ihrer Einschätzungen zu berücksichtigen. Obwohl diese Methode nur unter bestimmten Voraussetzungen verwendet werden kann, stellt sie doch eine Möglichkeit dar, um die Parametrisierung von anderen Bayes'schen Netzen voranzubringen. Diese Arbeit behandelt auch das Thema der Übersichtlichkeit von großen Bayes'schen Netzen. Der kurze Vergleich soll weder eine Art von Bayes'schen Netzen oder eine Software empfehlen, sondern vielmehr auf die Notwendigkeit hinweisen, die Anwendbarkeit und Benutzerfreundlichkeit großer Modelle zu berücksichtigen.

Die Fallstudie in Nordwestchina zielte auch darauf ab, lokale Grünflächenplaner zu unterstützen und zu informieren. Es ist schwierig abzuschätzen, inwiefern diese Fallstudie zum lokalen Umweltmanagement beitragen konnte. Die Forschungsumstände in Nordwestchina machten es unmöglich, dieselbe

Expertengruppe zu allen Workshops einzuladen. Die hohe Fluktuation der Workshopteilnehmer minderte sicherlich das Zugehörigkeitsgefühl („*ownership*") zum Modellierungsprozess und die Akzeptanz der Modellergebnisse. Dennoch stellte jeder Workshop eine Plattform für Diskussionen und gegenseitiges Lernen dar. Wie in vielen anderen partizipativen Anwendungen von Bayes'schen Netzen war die Möglichkeit zum Wissensaustausch zwischen den Workshopteilnehmern mindestens genau so wertvoll wie die Modellergebnisse selbst.

Table of contents

List of figures

Figures in Appendices A – G

List of tables

Tables in Appendices A – G

List of abbreviations and acronyms

ACT	Australian Capital Territory
AI	Artificial Intelligence
ANU	Australian National University
BDN	Bayesian Decision Network
BN	Bayesian Network
CPT	Conditional probability table
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DAG	Directed acyclic graph
DBN	Dynamic Bayesian Network
DI	Discomfort Index
ECD	Ecological Character Description
e.g.	For example (Latin: *exempli gratia*)
EM	Expectation-maximization
ESLT	Environmentally sustainable levels of take
ESS	Ecosystem services
EU	(total) Expected utility
iCAM	Integrated Catchment Assessment and Management Centre
ICI	Independence of causal influence
MDB	Murray-Darling Basin
MDBA	Murray-Darling Basin Authority
n.d.	No date
NSW	New South Wales
NW China	Northwest China
OOBN	Object-Oriented Bayesian Network
PT	Probability table
QLD	Queensland
RQ	Research question
SA	South Australia
SuMaRiO	Sustainable Management of River Oasis along the Tarim River
TEEB	The Economics of Ecosystems and Biodiversity
UHI	Urban Heat Island
VIC	Victoria
WS	Workshop

1. Introduction

Today's environmental problems are complex and pose urgent challenges to environmental managers. As nature and society are diversely interrelated, it is difficult to anticipate or predict all natural responses to anthropogenic influences and vice versa. Thus, environmental managers often need to choose between several management options – without having full knowledge of the consequences. Computer-based environmental models, such as Bayesian Networks (BNs), are a means to assist environmental managers to make more informed decisions under uncertainty (e.g. Carmona et al., 2013). There are two reasons why BNs are increasingly used for environmental and ecological modeling (Aguilera et al., 2011; McCann et al., 2006). First, BNs are probabilistic causal models in which the relationships between variables are expressed in conditional probabilities. By describing these relationships in a probabilistic way, the above-mentioned uncertainty inherent in complex nature-society systems can be explicitly addressed. Second, BNs accept various input data types, including expert and stakeholder knowledge, and therefore allow the utilization and combination of the best data available. This helps to develop and quantify models under data scarcity. The experiential knowledge of experts and stakeholders does not solely complement or substitute for data. Involving multidisciplinary experts and stakeholders from various fields in environmental modeling processes also helps to better understand complex environmental problems and to jointly find a holistic solution to them (Laniak et al., 2013).

Integrating expert and stakeholder knowledge into BNs is a discipline of its own. Over the past decade, BNs have increasingly been used to integrate experts' knowledge from various disciplines as well as diverging problem perspectives (Ban et al., 2014; Grêt-Regamey et al., 2013; Haapasaari et al., 2013; Henriksen et al., 2007). In the past decade, a multitude of consultation and elicitation formats were used to derive conditional probabilities from expert knowledge (see Chapter 3). However, most of these elicitation methods require a very high commitment of time – both from experts and modelers. This thesis therefore seeks to improve the expert elicitation of BN parameters under serious time constraints. In addition to developing "expert-friendly" elicitation methods, the thesis aims at improving the "user-friendliness" of complex BNs by combining different BN types and BN software.

This introductory chapter first reflects on the role of expert and stakeholder knowledge in environmental modeling (Chapter 1.1). It highlights both the methodological motivation behind the present thesis and the real-world purpose pursued by it (Chapter 1.2). The chapter presents the research questions which were addressed by two case studies in Northwest China and Australia (Chapter 1.3) and provides an outline of the thesis (Chapter 1.4).

1.1 The role of experts and stakeholder knowledge in environmental modeling

A literature review revealed that experts and stakeholders are attributed with different functions in environmental modeling. To highlight their differing roles, this chapter first provides a definition on who are “experts” and “stakeholders” (Chapter 1.1.1). It briefly summarizes different motivations behind expert and stakeholder engagement (Chapter 1.1.2) and highlights the strengths and weaknesses of expert-based models (Chapter 1.1.3).

1.1.1 Experts and stakeholders

The term “expert” classifies persons according to their expertise, while the term “stakeholder” is used in the context of decision-making processes. Throughout this thesis, an “expert” is someone who has gained specialized, in-depth knowledge of the topic of interest (Drew and Perera, 2012; Krueger et al., 2012). This broad definition focuses on personal experience – no matter whether it is gained through research work or practical experience in the field. Therefore it includes experts working in academia, such as researchers from universities and research institutes, and experts working outside academia, such as environmental planners and natural resource managers.

In contrast, a “stakeholder” is someone who either has the power to influence processes or actions or who is affected by them (Freeman, 1984 as cited in Krueger et al., 2012). This definition classifies stakeholders into those who affect and those who are affected. It acknowledges that stakeholders, such as farmers, who are not “influential” in terms of having the power to influence decision-making, still are “important” for the implementation of these decisions. Thus, the involvement of influential and important stakeholders in modeling processes (1) helps to understand complex problem fields, e.g. by eliciting differing problem perspectives from conflicting stakeholder groups (Baran et al., 2006), and (2) increases the chance that model results are put into use after the modeling process has ended. Details on importance and influence of different stakeholder groups for natural resource management are provided by the works of Grimble and Wellard (1997) and Grimble (1998).

The terms “expert” and “stakeholder” do not exclude each other. Stakeholders can be experts, while experts can have a stake in a certain process or action. In general, natural resource planners and managers as well as persons with technical background were ascribed a higher level expertness or competence among all stakeholder groups (e.g. Chan et al., 2010).

1.1.2 Motivations behind expert and stakeholder involvement

Due to the pressing nature of environmental problems and the prevalent data scarcity, BN modelers often use numerous knowledge sources available – ranging from scientific literature, model outputs, empirical data or expert and stakeholder knowledge (Borsuk et al., 2004; Carmona et al., 2013; Hamilton et al., 2007). Involving experts and stakeholders from various disciplines and working fields helps to better understand complex problems, to develop more-informed models under data scarcity and to jointly find holistic solutions to real-world problems. In some cases, the general public is also involved, e.g. to identify variables of interest (Borsuk et al., 2001) or to increase the acceptance of management decisions arising from the modeling process or final model results (Henriksen et al., 2007).

A literature review revealed different motivations behind engaging experts and stakeholders in environmental modeling processes. Whereas expert knowledge is mostly used under data scarcity to complement or even substitute for other data sources (Drew and Perera, 2012), stakeholders are mainly involved in modeling processes that aim at supporting decision-making and decision implementation (Voinov and Bousquet, 2010). However, this statement is not universally valid. Some expert-based modeling processes support decision-making (Chan et al., 2012; Hamilton et al., 2007; Holzkämper et al., 2012) and some stakeholder-based BN applications solely aim at knowledge elicitation (Castelletti and Soncini-Sessa, 2007b).

The degree to which experts and stakeholders are involved in modeling processes also reflects the motivation behind their engagement. Using the terminology of Lynam et al. (2007), the involvement may solely be an “extractive use” of knowledge, which is a one-way elicitation, or “co-learning” or even “co-management”, depending on the level of expert/stakeholder interaction and their influence on decision-making processes. In BN applications in which expert knowledge is elicited in individual meetings (Jensen et al., 2009; Pellikka et al., 2005; Pike, 2004), the main motivation is to simply “extract” their knowledge as alternative to missing data. In contrast, BN applications come closer to the goal of co-learning and co-management if a broad range of experts and stakeholder groups are gathered for joint discussions and elicitation procedures (Baran et al., 2006; Carmona et al., 2013; Murray et al., 2012).

Most BN applications in which expert knowledge served as sole input data were carried out in the field of ecology (Allan et al., 2012; Amstrup et al., 2008; Jensen et al., 2009; Johnson et al., 2010; Pellikka et al., 2005). One reason for this is that long-term ecological data sets are often lacking due to financial and logistical constraints (Martin et al., 2005). Another reason is that specific knowledge of rare species might not be published but existent in the form of experiential knowledge. Experts are therefore regarded as “most accessible and cost-effective source of immediate ecological information” (Drew and Perera, 2012: 230).

In general, expert knowledge has a higher reputation than stakeholder knowledge. Whereas expert knowledge is regarded as best estimate available and legitimate alternative to "hard data" (Borsuk et al., 2003; Bromley, 2005), in some BN applications, stakeholder knowledge, in the form of a jointly developed network structure or elicited conditional probability values, was revised or validated by experts (Baran et al., 2006; Nash et al., 2010).

1.1.3 Advantages and disadvantages of using expert knowledge

The main advantage of expert-based BN modeling is its cost and time efficiency (see Chapter 1.1.2). Through expert elicitation, the aggregated knowledge of many years of experience can be utilized, including experience gained outside the study region (Martin et al., 2005). Expert elicitation discloses information for which no measured data equivalent is available or accessible (Krueger et al., 2012) – at least within the temporal and financial constraints of a given research project. Under data scarce conditions, BNs can be developed, parameterized, and run based on expert knowledge only. An expert-based BN is often referred to as "alpha-level model" (Marcot et al., 2006) or "first generation model" (Amstrup et al., 2008) which can be updated as soon as other data has become available.

The major disadvantage of using expert knowledge is the related risk of inaccuracy, overconfidence and expert biases. Expert knowledge can be inaccurate, just as measurements can be imprecise and data sets can be insufficient (Burgman, 2005; O'Hagan et al., 2006). Burgman et al. (2011) found out that common "quality criteria" of experts, such as qualifications, years of experience and track record, do not necessarily correspond with their actual performance in estimating quantities, natural frequencies and probabilities relevant to their fields of expertise. However, the overall performance of predictions, improved substantially following group discussion in all cases. In their comparison of expert reputation and performance, Burgman et al. (2011) also revealed that experts' performance in giving accurate estimates was highly overrated by society as well as by experts themselves. In the elicitation of probabilities, it is relatively easy to recognize overconfidence, e.g. if experts tend to make extreme estimates, such as near zero or near 100 % (Morgan and Henrion, 1990). With respect to biases, experts might try to dominate group discussions to modify the model according to their own goals (intentional biases) or experts might be too confident in their own knowledge (unintentional biases) (Burgman, 2005). These problems can be taken care of by an experienced moderator during group discussions.

1.2 Motivation and purpose behind the present thesis

As the case studies conducted in Northwest China and Australia differ in time spent, depth of study, and findings, it was never intended to compare them. Despite these differences, they share a common ground in methodology and on the subject level. Both case studies use Bayesian Networks (BNs) and focus on ecosystem services (ESS) which are broadly defined as benefits that people obtain from ecosystems (Millennium Ecosystem Assessment, 2005). The case studies are both included in the thesis to present varying challenges of expert-based BN modeling and different approaches to handle them.

This chapter highlights the different methodological motivations and real-world purposes behind the two case studies. Here, the "methodological motivation" is the ambition to address methodological research gaps, while the "real-world purpose" is the aim to address existing environmental problems and to contribute to their solutions.

1.2.1 Case study Northwest China

The Northwest China case study was designed as a three-year study in the frame of the SuMaRiO project (Sustainable Management of River Oasis along the Tarim River, China). The SuMaRiO project is part of the "Sustainable Land Management" funding measure sponsored by the Federal Ministry of Education and Research (dt. Bundesministerium für Bildung und Forschung). One of SuMaRiO's main objectives is to develop methods to assess ecosystem services (ESS) and to support the integration of the ESS concept into land and water management in the water-scarce Tarim Basin in Xinjiang Uighur Autonomous Region, Northwest China (Siew and Döll, 2012). Accordingly, this case study aimed at developing, applying, and evaluating participatory modeling methods to support sustainable environmental management in the case study region.

The methodological challenge of this case study was to develop a BN under data scarcity and with few chances to meet local experts – and only for a short time. Many participatory BN applications are impeded by the discrepancy between time available and time needed for developing fully-functioning BNs with experts and stakeholders. Especially the elicitation of conditional probability values is very time-consuming and cognitively challenging for experts and stakeholders (Grêt-Regamey et al., 2013; Uusitalo, 2007). As a consequence, some participatory BNs remain half-finished. For example, Cain et al. (2003) described how only one of four stakeholder groups managed to develop a complete BN during a six-hour-workshop. The methodological motivation behind this case study therefore was to develop a simple and robust method for deriving conditional probability tables from expert estimates. As the BN modeling process in Northwest China had to be conducted in three 3-hour-workshops, it was predestined for testing "expert-friendly" elicitation formats that can be used under serious time constraints.

The real-world purpose of the case study was to support and inform local urban and peri-urban vegetation managers and planners. The purpose of the BN model was defined in accordance with the needs of local urban landscape planners. In an interview, they explicitly asked for a model that compared plant species in their ability to mitigate dust weather and their irrigation needs. As oasis towns in Southern Xinjiang, such as Aksu and Korla, are exposed to dust weather approximately 100 days per year (Yabuki et al., 2005), dust weather mitigation is one of the most relevant ecosystem services in the region. The term dust weather describes dust events in which desert dust particles are raised and transported by the wind. Although local vegetation managers seemed to be mainly interested in dust mitigation, urban and peri-urban vegetation provides many more ecosystem services for people living in oasis towns at the margin of the Taklamakan desert (Halik, 2003). For example, temperatures in these oasis towns reach 40°C or higher during summer months. Under the impact of climate change, it is most likely that the arid region of the Taklamakan desert would even experience higher temperatures. Therefore, this case study also addressed the role of urban vegetation in reducing urban heat stress by providing shade. This might be of local relevance and interest in the future.

1.2.2 Case study Australia

The Australia case study was conducted during a three-month research stay at the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Integrated Catchment Assessment and Management Centre (iCAM) at the Australian National University (ANU) in Canberra, Australia. The author's intention behind this research stay was to learn from and exchange with Australian experts in BN modeling. The methodological motivation behind this particular study was to exhaust the potential of large BNs to model multiple ecosystem services (ESS) simultaneously which has not been explored by previous BN applications in ESS modeling (Landuyt et al., 2013). In addition, the size of the final BN provided the opportunity to compare different BN software tools with regard to presentation clarity or "user-friendliness". The real world purpose was minimal due to the short project time. Although the subject of managing ecosystems and environmental flows in the Murray-Darling Basin is of interest to many local stakeholders, the BN was solely developed in cooperation with an ecological modeler.

1.3 Research questions

In accordance with the methodological motivations behind the two case studies, this thesis addresses two sets of research questions (RQs). The first set of questions is related to easing expert elicitation processes and the second to improving user-friendliness of (large) BNs. The two primary research questions (RQ 1 and RQ 2) are subdivided into two secondary research questions each which are addressed by various chapters of this thesis (see Table 1).

RQ 1: How to improve expert-based parameters in Bayesian Networks?

RQ 1.1: How to improve the efficiency of modeling processes for expert-based Bayesian Networks?

RQ 1.2: How to increase the reliability of expert-based parameters in Bayesian Networks?

RQ 2: How to improve the user-friendliness by combining Bayesian Network types and software tools?

RQ 2.1: What are the pros and cons of a combined application of Bayesian Networks (BNs) and Bayesian Decision Networks (BDNs)?

RQ 2.2: What are the pros and cons of different software tools with regard to presentation clarity of large Bayesian Networks?

Table 1: Overview of secondary research questions and related thesis chapters.

Research question	Case study	Approach	Discussion
RQ 1.1	NW China	Development and application of new elicitation format (see Chapter 4.2.3.1)	Chapter 4.6.1
RQ 1.2	NW China	Development and application of new confidence-based conversion method (see Chapter 4.2.3.1 and Chapter 4.4.1.2)	Chapter 4.6.2
RQ 2.1	NW China	Combined application of BNs and BDNs (see Chapter 4.3.1)	Chapter 4.6.3
RQ 2.2	Australia	Comparison of two BN software tools, Netica and GeNie, with regard to user-friendliness of large BNs (see Chapter 5.3)	Chapter 5.4

1.4 Outline of the thesis

The thesis is organized in six chapters and presents the results of two case studies conducted in Northwest China and Australia. Chapter 2 provides a technical overview of Bayesian Network modeling. This methodological chapter builds the foundations for all following chapters by first presenting components of Bayesian Networks (BNs), by explaining the basics of model parameterization and model sensitivity, and by introducing different BN types. Chapter 3 depicts the results of a thorough literature review on expert-based BN modeling in support of environmental management. The identified consultation and elicitation formats and the insights on how other BN applications combined expert knowledge serve as background for the discussion in the subsequent chapter. The largest part of this thesis, Chapter 4, presents the case study which was conducted in Northwest China from 2011 to 2014. This self-contained chapter starts with a brief description of how the research conditions in the case study region affected the BN modeling process. The following step-by-step documentation provides insights of how experts informed the network structure and model parameters. The chapter introduces and discusses new methods for the elicitation of expert estimates and the systematic conversion of these estimates into conditional probability values. The chapter concludes with a reflection on what has been learned in the course of the modeling process. Chapter 5 presents the results of a three-month research stay in Australia. After providing background information on environmental flow management and ecosystem services in the Murray-Darling Basin, it describes the structure of the final BN with the help of four sub-networks and discusses the issue of presentation clarity of large BNs. Finally, Chapter 6 briefly assesses the contributions achieved by this thesis.

2. Bayesian Networks[1]

The term “Bayesian” refers to the 18th century mathematician and clergyman Thomas Bayes (1702-1761). Bayes’ posthumously published work “An Essay towards Solving a Problem in the Doctrine of Chances” introduced a new approach to probability as well as a formula for belief updating, later referred to as Bayes’ Theorem or Bayes’ rule (Bayes and Price, 1763). The Bayesian approach to probability defines probability as someone’s degree of belief that an event will occur in the future. This stands in contrast to the frequentist approach which defines probability as frequency or proportion of times that an event occurs when an experiment is repeated (O'Hagan et al., 2006). Whereas the frequentist approach attaches importance to data, the Bayesian approach acknowledges expert beliefs as knowledge source to be used to predict future events in the absence of data. The idea that belief comes in degrees also implies that human opinion is constrained by ignorance and highlights the necessity to quantify uncertainty about unknown parameters in the form of a probability distribution (Korb and Nicholson, 2011; O'Hagan et al., 2006).

A Bayesian Network (BN) is a probabilistic causal model of a selected real system. The system’s components and the relationships between them are represented in the form of a causal network. In a BN, a link between two variables indicates that one variable is conditionally dependent on the other. The strength of conditional dependence is expressed in conditional probabilities. With the help of Bayes’ rule, BNs apply Bayesian inference which is the recalculation or updating of all probabilities whenever new knowledge or data on any variable in the network is acquired (see Chapter 2.3). BNs emerged from Artificial Intelligence (AI) research (Minsky, 1961; Pearl, 1982) and were first applied for diagnostic purposes, e.g. in the fields of medicine and fault diagnosis (Fenton and Neil, 2007: 12ff.). Since the late-1990s, BNs are increasingly being used in environmental modeling and natural resources management as they offer the possibility (1) to explicitly express uncertainty, (2) to integrate and combine a wide range of input data types and (3) to integrate experts’ knowledge within participatory modeling processes (Aguilera et al., 2011; Düspohl et al., 2012; Uusitalo, 2007).

This chapter briefly introduces the components of Bayesian Networks (BNs) (Chapter 2.1); it shows how BN software generates conditional probability tables (CPTs) from data and equations (Chapter 2.2), how BNs are used for top-down and bottom-up modeling (Chapter 2.3), and how model sensitivity is usually analyzed (Chapter 2.4). In addition, it provides a short overview of different BN types (Chapter 2.5).

[1] Parts of this chapter, namely text passages of chapter 2.1, 2.3, and 2.5.1 are extracted from the author’s contributions to Düspohl et al. (2012) and Frank et al. (2014a).

2.1. Components of Bayesian Networks

BNs consist of three elements (Cain, 2001): (1) System variables referred to as nodes and visualized as boxes, (2) causal relationships between these nodes visualized as directed links which point from cause to effect, and (3) a set of (conditional) probabilities, for each node, defining the strength of the causal relationships. As BNs are directed acyclic graphs (DAGs), feedback loops are not possible in the networks.

For BN modeling a large number of BN software packages exists (Fenton and Neil, 2007; Uusitalo, 2007). In the field of environmental modeling, the software Netica and Hugin are most frequently used (Aguilera et al., 2011). The BNs presented in this chapter are generated using Netica™ Version 4.6 (Norsys, http://www.norsys.com). The software depicts variables in beige rectangles which are called nature nodes. The probability distribution across states is shown as a %-probability and visualized with black horizontal bars, which are referred to as *belief bars*. Figure 1 is an example of a BN (network structure and states of the variables) that models the decision of a reviewer to accept or reject a scientific paper.

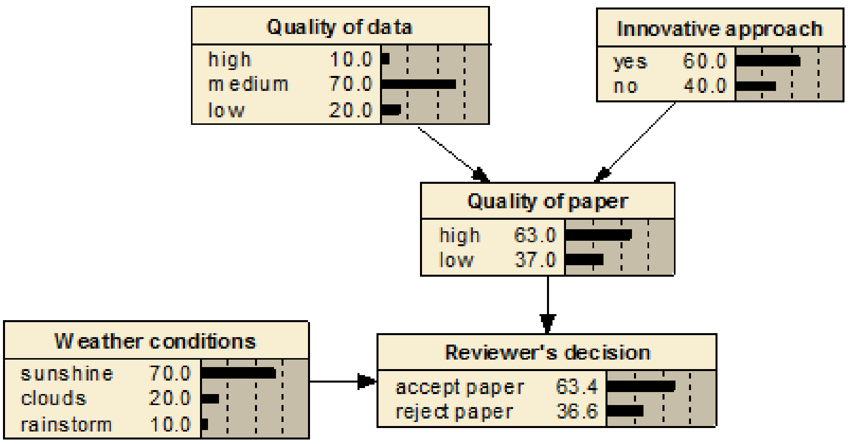


Figure 1: A simple Bayesian Network “Reviewer’s decision”.

The diagram indicates that the system variable “Reviewer’s decision” is influenced by the “Quality of the paper” as well as by “Weather conditions” which influence the reviewer’s mood and thus decision. The directed links between the nodes indicate causal relationships. In this case, the nodes “Quality of the paper” and “Weather conditions” are the parent nodes of “Reviewer’s decision”, while “Reviewer’s decision” is their child node. Nodes without parent nodes, such as “Quality of data”, “Innovative approach”, and “Weather conditions”, are called root nodes. Nodes without child nodes, such as “Reviewer’s decision”, are called leaf nodes. Root nodes represent the input variables, while leaf nodes constitute the output variables of the BN (Castelletti and Soncini-Sessa, 2007a).

Variables (i.e. nodes) can be either continuous or discrete (as in Figure 1), and in most BN applications, discrete variables are described by a limited number of discrete states (e.g. two in the case of "Reviewer's decision"). States for discrete nodes can either be (1) labels, e.g. "low, medium, high", (2) numbers, (3) intervals, or (4) in Boolean form (e.g. "yes, no") (Bromley, 2005). The states must encompass all possible conditions and must be mutually exclusive.

For each child node, conditional probability tables (CPTs) need to be defined. A CPT expresses the probability for the states of a child node, given the states of its parent nodes. The rows of a CPT can be read as "if-then-sentences". In our example, the CPT of "Reviewer's decision" reveals that "If the quality of the paper is high and the sun is shining, then the paper will be accepted with a probability of 95%" (Table 2). The CPT shows the strengths of the causal relationships, with the "Quality of the paper" having a much stronger impact on the decision than the "Weather conditions".

Table 2: Conditional probability table of node "Reviewer's decision".

Quality of paper	Weather conditions	accept paper	reject paper
high	sunshine	95	5
high	clouds	90	10
high	rainstorm	85	15
low	sunshine	15	85
low	clouds	10	90
low	rainstorm	5	95

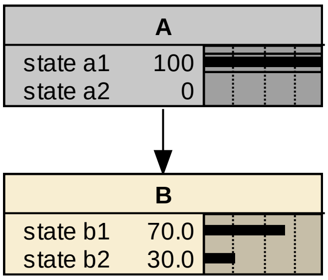
Root nodes are quantified by unconditional probability tables (PTs) which can represent observations, scenarios, or potential actions such as management interventions (Bromley, 2005). If root nodes are used to represent different scenarios of the future, the states can also be anchored to the current conditions, for example with labels such as "lower than today", "like today", and "higher than today" (Cain, 2001).

2.2. Model parameterization

For the model parameterization – in jargon known as population of probability tables – all kinds of data can serve as model input: Outputs from other models, data derived from statistics, measurements, scientific literature or household surveys, as well as expert and stakeholder knowledge. Although the BNs presented in this thesis are mainly populated with expert knowledge, for completeness, this chapter briefly introduces how Netica "learns" parameters by counting (Chapter 2.2.1) and builds CPTs from equations (Chapter 2.2.2).

2.2.1. Parameter learning by counting

Netica uses three algorithms to generate or "learn" CPTs from data: Counting-learning, expectation-maximization (EM) and gradient descent (Norsys Software Corp., 2010: 46ff.). The counting-learning algorithm, also referred to as Lauritzen and Spiegelhalter algorithm, is most widely used to learn CPTs from case files (Korb and Nicholson, 2011: 189). A case is defined as "set of all findings entered into the nodes of a single Bayes' net" (Norsys Software Corp., 2010: 36) and a case file consists of more than one or many cases.



A	state b1	state b2
state a1	70	30
state a2	30	70

Figure 2: On the left, Bayesian Network with two nodes (A, B) and two states each (a1/a2, b1/b2); on the right, conditional probability table of node B.

Here, a simulated case file with 100 cases[2] (Table 3) is incorporated into the example BN[3] (Figure 2). In 35 of 50 cases, state a1 leads to state b1 (70%) and in 15 cases state a1 leads to state b2 (30%). Thus, Netica counts the frequency with which combinations of the parent states lead to each state of the child node.

[2] Netica ► Cases ► Simulate cases.
[3] Netica ► Cases ► Incorp case file.

For parameter learning, Netica requires a large amount of data about the parent nodes and their corresponding child nodes. Whereas the counting-learning algorithm ignores cases in which states of child or parent nodes are missing, the EM algorithm estimates missing values from available data. For a comparison of the performances of the counting-learning and the EM algorithm, see Ticehurst et al. (2011).

Table 3: Simulated file with 100 cases.

NumCases	A	B
35	state_a1	state_b1
15	state_a2	state_b1
15	state_a1	state_b2
35	state_a2	state_b2

2.2.2. Building conditional probability tables from equations

Netica needs three pieces of information to build a conditional probability table (CPT) for a child node: (1) Assigned state values ("state numbers") for each state of the parent nodes, (2) an equation to be used for the respective child node, and (3) assigned discretization intervals for each state of the child node. The following working steps are necessary to build the CPT of node C for Figure 3 from an equation. In this example, node C is a "summary node" which subsumes the impact of all parent nodes – here with the help of a simple equation.

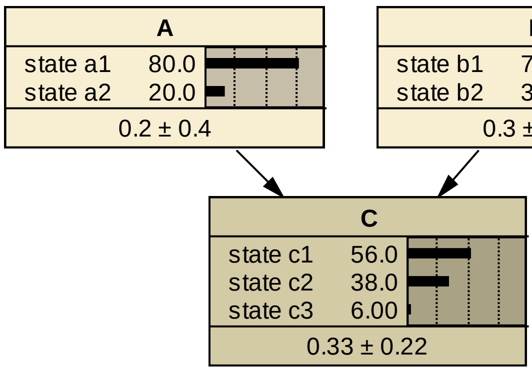


Figure 3: Bayesian Network with three nodes (A, B, C) and two states each (a1/a2, b1/b2, c1/c2).

(1) Each state of the parent nodes A and B needs an assigned state value ("state number"). Here, the value 0 is attached to the states a1 and b1; the value 1 is assigned to the states a2 and b2 (Table 4). In Netica, the states of the parent nodes need to be arranged in the same order – for example from least favorable

to most favorable. If the labels “low”, “medium”, and “high” are used, the states should consistently start with “low”.

Table 4: States and state numbers of node A and B of Figure 3, with maximum state numbers underlined.

A			B	
State	State number		State	State number
state a1	0		state b1	0
state a2	<u>1</u>		state b2	<u>1</u>

(2) To build the CPT of node C, an equation is entered in the equation window of its node dialog box: C (A, B) = (A+B)/2 (1)
This equation divides the sum of the state numbers of each state by the sum of the maximum state numbers, here the value 2 (1+1 = 2). The calculation is presented in Table 5. If the same state values are assigned to all parent nodes, they are equally weighted.

(3) To use an equation, node C needs to be continuous. However, to convert each calculated ratio from the equation (1) into discrete states, node C needs assigned discretization intervals between 0-1 for each state. Here, the discretization values 0, 0.33, 0.66, and 1 are chosen for state c1 (0-0.33), state c2 (0.33-0.66) and state c3 (0.66-1). This way, the value 0 leads to state c1 (discretization interval 0-0.33) with a probability of 100% as shown in the first row of Table 5.

(4) Netica builds the CPT from the equation with the command “Equation to table”[4]. Deterministic CPTs are by default represented as so-called *function tables* which show the calculated values of the equation (Table 5). Function tables can be switched into %-probability tables with the respective selector in the table dialog box.

[4] Netica ► Table ► Equation to table.

Table 5: Calculation of equation (1) to build the function table and the conditional probability table of node C of Figure 3, both marked in pastel orange.

State (state number)		Calculation of equation	Function table	Conditional probability table (%)		
A	B	C (A, B) = (A+B)/2		state c1 (0-0.33)	state c2 (0.33-0.66)	state c3 (0.66-1)
state a1 (0)	state b1 (0)	C(a1,b1) = (a1+b1)/2 = (0+0)/2 = 0	0	100	0	0
state a1 (0)	state b2 (1)	C(a1,b2) = (a1+b2)/2 = (0+1)/2 = 0.5	0.5	0	100	0
state a2 (1)	state b1 (0)	C(a2,b1) = (a2+b1)/2 = (1+0)/2 = 0.5	0.5	0	100	0
state a2 (1)	state b2 (1)	C(a2,b2) = (a2+b2)/2 = (1+1)/2 = 1	1	0	0	100

After the CPT of node C has been built from an equation, Netica uses the probability tables of the parent nodes A and B and the CPT of node C to calculate the probability distribution of the child node (see Chapter 2.3 for calculations). If the probabilities of state a1 and b1 are set to 100% (Figure 4), the probability that node C is in state c1 is 100% because of its deterministic table (Table 5). When the probability of a certain state is set to 100%, the color of the node changes to gray (compare Figure 3 and Figure 4).

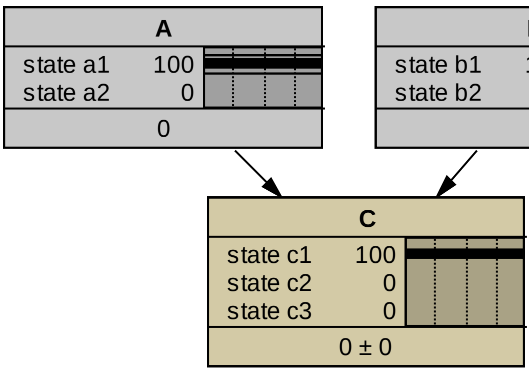


Figure 4: The same Bayesian Network as in Figure 3 after having set the probabilities of state a1 and b1 to 100%.

Due to the equation, node C needs to be continuous and its CPT becomes deterministic which is indicated by the brown color of the node (Figure 3). For continuous nodes and nodes with assigned state values, the mean value followed by ± and the standard deviation (Norsys Software Corp., n.d.)[5] are shown below the belief bars. In Figure 3, node A displays the mean value (0.2) and its standard deviation (0.4). Table 6 shows how Netica calculates these values using the assigned state values and their probabilities.

Table 6: Calculation of mean value, variance and standard deviation for discrete node A of Figure 3.

State	State value (x)	Probability (P) $P(x)$	Mean value (μ) $\mu = \sum_x xP(x)$	Variance (V) $V = \sum_x (x-\mu)^2 p(x)$	Standard deviation (σ) $\sigma x = \sqrt{V}$
state a1	0	0.8	0*0.8 = 0	$(0\text{-}0.2)^2$*0.8 = 0.032	
state a2	1	0.2	1*0.2 = 0.2	$(1\text{-}0.2)^2$*0.2 = 0.128	
$\sum$		= 1	= 0.2	= 0.16	= $\sqrt{0.16}$ = 0.4

2.3. Top-down and bottom-up modeling

BNs can either be applied for predictive purposes ("top-down modeling") or for diagnosis ("bottom-up modeling") (Castelletti and Soncini-Sessa, 2007a). For top-down modeling, root nodes are used to compare scenarios of the future or management options. It is therefore appropriate for impact and scenario analyses, where the BN computes the impact of management decisions, represented by states of the root nodes, on the variables that are planned to be optimized. To compare the effects of these management decisions, the probability of each state of the root node can be set to 100% (one after the other) to see how the probability distribution of the child or leaf node of interest changes. Bottom-up modeling is applied for diagnostic purposes, e.g. to assess the likely reasons for an observed environmental pollution. For example, if an observation has been made for a leaf node, the probability distributions in the root nodes indicate the most likely cause for the observation. This is not equivalent to optimization, i.e. the updated probability distributions of the root nodes cannot be interpreted in terms of decisions that would lead to the observed finding or any desired state of the leaf node.

For top-down modeling or downward propagation, the BN software applies the fundamental rule of probability and a joint probability calculation (Jensen and Nielsen, 2007). This calculation is not only used to recalculate probability distributions after the probability of a root node state is set to 100%, but also to calculate the probability distributions of the child nodes in the first place. For calculating the probability

[5] Netica's Help System ► Reference ► Encyclopedia ► Standard Deviation.

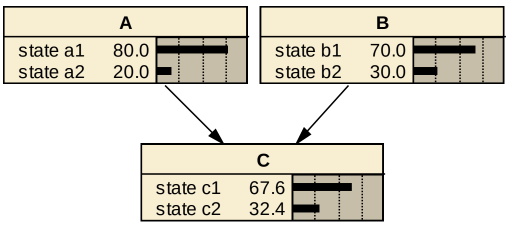
distribution of child node C (Figure 5), Netica needs its conditional probability table P (C|A,B) and the unconditional probability tables of the parent nodes P (A) and P (B).

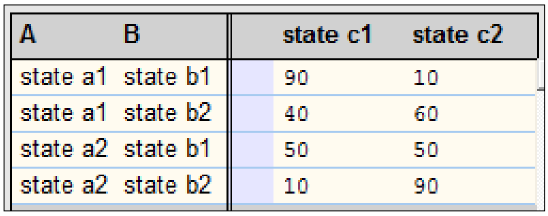
First, the BN software uses the fundamental rule of probability (2) to calculate the joint probability: P (A,B,C) = $P(C|A,B) * P\ (A) * P(B)$

Then the software *marginalizes* the probabilities of each state of P (C) out of the joint probability P (A,B,C) (Jensen and Nielsen, 2007). In general, the term marginalization describes the summation of values along rows (or columns) in tables. These sums are written in an extra column (or row) at the margins of a table. Table 7 elucidates the joint probability calculus and presents the marginalized probabilities of P (C) out of P (A,B,C) at the right margin of the table.

For bottom-up modeling or upward propagation, the BN software applies the Bayes' rule (3) to recalculate all probability distributions after the probability of a state in one node, here leaf node, is set to 100% (Figure 6) (Jensen and Nielsen, 2007):

$$\mathrm{P(A|B)} = \frac{\mathrm{P(B|A)*P(A)}}{\mathrm{P(B)}} \qquad (3)$$





A	B	state c1	state c2
state a1	state b1	90	10
state a1	state b2	40	60
state a2	state b1	50	50
state a2	state b2	10	90

Figure 5: On the left, Bayesian Network with three nodes (A, B, C) and two states each (a1/a2, b1/b2, c1/c2); on the right, conditional probability table of node C.

Table 7: Joint probability calculation with the fundamental rule (2) and marginalization of P (C) out of P (A,B,C) of Figure 5.

	a1		a2		P(C)
	b1	b2	b1	b2	$P(C) = \sum_{A,B} P(A,B,C)$
c1	P(a1,b1,c1) = P(c1|a1,b1)* P(a1)*P(b1) = 0.9*0.8*0.7 = 0.504	P(a1,b2,c1) = P(c1|a1,b2) *P(a1)*P(b2) = 0.4*0.8*0.3 = 0.096	P(a2,b1,c1) = P(c1|a2,b1)* P(a2)*P(b1) = 0.5*0.2*0.7 = 0.07	P(a2,b2,c1) = P(c1|a2,b2)*P (a2)*P(b2) = 0.10*0.20*0.3 = 0.006	0.676 (= 67.6%)
c2	P(a1,b1,c2) = P(c2|a1,b1)* P(a1)*P(b1) = 0.1*0.8*0.7 = 0.056	P(a1,b2,c2) = P(c2|a1,b2) *P(a1)*P(b2) = 0.6*0.8*0.3 = 0.144	P(a2,b1,c2) = P(c2|a2,b1)* P(a2)*P(b1) = 0.5*0.2*0.7 = 0.07	P(a2,b2,c2) = P(c2|a2,b2)* P(a2)*P(b2) = 0.90*0.20*0.3 = 0.054	0.324 (= 32.4%)

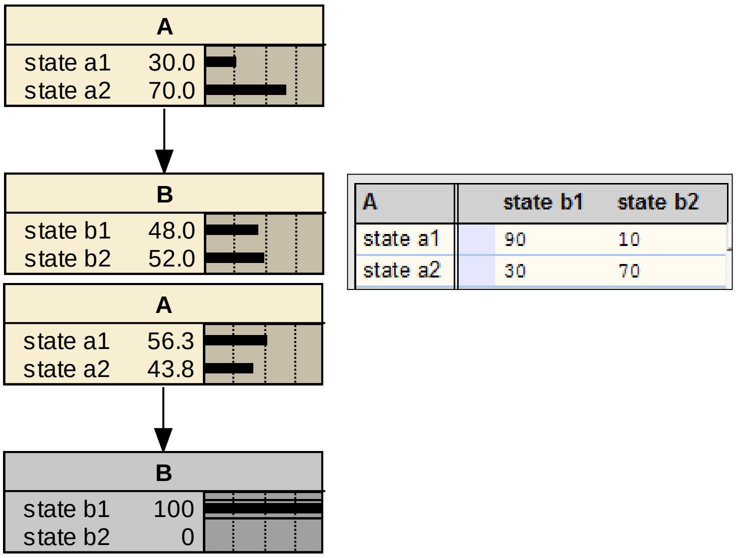


Figure 6: Bottom-up modeling with the Bayes' rule (3).
At the top, Bayesian Network before an observation has been made (left) and conditional probability table of node B (right). At the bottom, result of the recalculation of P(A) after an observation has been made for node B.

Table 8: Recalculation of P(A) after an observation has been made for node B of with the Bayes' rule.

	b1
a1	P(a1|b1) = P(b1|a1)*P(a1)/P(b1) = 0.9*0.3/0.48 = 0.5625 (= 56.3%)
a2	P(a2|b1) = P(b1|a2)*P(a2)/P(b1) = 0.3*0.7/0.48 = 0.4375 (= 43.8%)

For bottom-up modeling, Netica uses the conditional probability P(B|A), the unconditional probability P(A) and the probability of B before an observation has been made for node B. Therefore, all probability values which are used for the recalculation of P(A) (Table 8) stem from the BN at the top of Figure 6.

2.4. Model sensitivity

Sensitivity analyses are used to investigate how sensitive a model output reacts to variations in the model input. As variables only react to changes in nodes of which they are conditionally dependent, this chapter briefly introduces how the network structure determines the information flows and thus the influence in a BN (Chapter 2.4.1).

BNs have two types of model input, probability distributions ("findings") of the other nodes and parameters (CPTs). This is the reason why two different types of sensitivity analyses can be performed. The first, "sensitivity to findings" shows how strongly the probability distribution of the query node is affected by changes in the probability distributions of other nodes (Chapter 2.4.2). The second, "sensitivity to parameters" shows how sensitive the probability distribution of the query node is to variations in other parameters (Chapter 2.4.3).

2.4.1. Information flows in Bayesian Networks

Entering new data or "findings" into a BN influences the information flow between the variables. This depends on the network structure or the way how variables are connected with each other. In BNs, directly linked variables indicate a direct causal connection. If nodes are linked via an intermediate variable, they can either be conditionally dependent or independent. This hinges on the way they are connected and whether or not the state of their intermediate variable is known (Castelletti and Soncini-Sessa, 2007a). There are three ways of connecting two variables via an intermediate variable: Serial, diverging, and converging connections (Charniak, 1991; Jensen and Nielsen, 2007; Koski and Noble, 2009).

In serial and diverging connections (Figure 7), all variables can influence each other as long as the state of the intermediate variable B is unknown. However, if the state of B is known, this communication channel or active trail is blocked, and A and C become separated and conditionally independent of each other, given B. This separation of variables in a directed graph is also referred to as d-separation (Jensen and Nielsen, 2007). In converging connections, the parent nodes A and C are independent as long as the state of B is unknown. However, if the state of B or of one of its child nodes is known, evidence can be transmitted through B and the parent nodes become dependent of each other. In this case, A and C can be regarded as competing causes of B. If the probability of A increases, the probability of C decreases. If cause A is known to have happened, cause C is less likely to have happened. This pattern of reasoning is called explaining away (Koski and Noble, 2009).

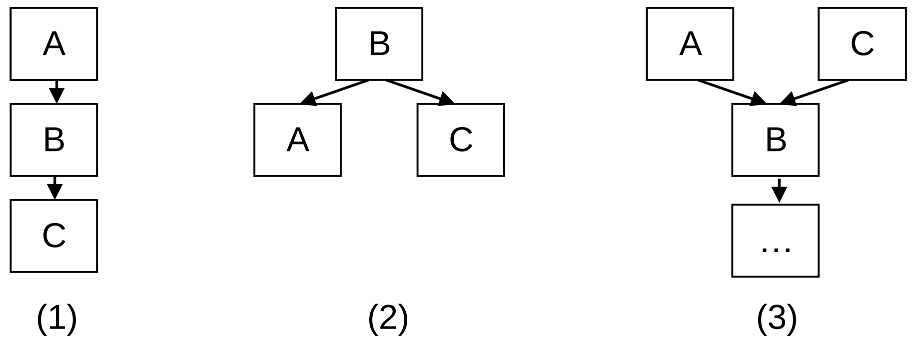


Figure 7: Three types of connections of two nodes (A and C) via an intermediate variable (B).
(1) Serial, (2) Diverging, and (3) Converging connection.

2.4.2. Sensitivity to findings

Netica uses two types of measures to quantify how much the probability distribution of the query node changes if a finding is entered at another node: Mutual information for discrete variables and variance reduction for continuous variables. For discrete node B of Figure 6, Netica determines the mutual information (I) of variables B and A with an entropy reduction calculation (4):

$$\mathrm{I}\,(A,B) \quad = \mathrm{H}\,(B) - \mathrm{H}\,(B|A) = \sum_B \sum_A P(A,B) \log_2 \left(\frac{P(B,A)}{P(B)P(A)}\right) \qquad (4)$$

with I (A,B) being the mutual information of variables A and B, and H being the entropy (Jensen and Nielsen, 2007: 251; Korb and Nicholson, 2011: 262; Norsys Software Corp., 2010: 47ff.). This way, Netica compares the entropy of B|A to what it would be if variable B was conditionally independent from A. The higher the mutual information of variables A and B, the more entropy or “randomness” of variable B is reduced by a finding at variable A (Pollino and Henderson, 2010: 14).

```
Sensitivity of 'B' to a finding at another node:

Node                Mutual      Percent    Variance of
----                Info                   Beliefs
B                   0.99885     100        0.2496000
A                   0.24124     24.2       0.0756000
```

Figure 8: Sensitivity to findings report for query node B of Figure 6.

The influence of node A on the probability distribution of the query node B depends on the conditional probability table P(B|A) and on the initial probability distribution of node A. For example, if node A has a uniform probability distribution (50:50) it has less influence on the query node B than it would have with a more distinct probability distribution, such as 90:10. This is because the query node would react more sensitive if a more distinct probability distribution was changed from 90:10 to 0:100. The influence of a node on the query node also depends on the number of intermediate or latent variables between them (Marcot et al., 2006). More details on this dilution effect can be found in the work of Bromley (2005: 77).

In Netica's sensitivity to findings report[6], the values are ranked according to their influence on the query node. For completeness, this report also includes the sensitivity of the query node (B) to changes at the query node itself (first row in Figure 8). As the minimum and maximum probability for each state of B is 0 and 1, the maximum reduction in entropy or variance is 100% (see "Percent" in Figure 8). In this case, the mutual information of B represents its full or maximum entropy with which the other values can be compared (Norsys Software Corp., n.d.)[7].

Sensitivity of 'C' to a finding at another node:

Node ----	Mutual Info	Percent	Variance of Beliefs
C	0.90868	100	0.2190240
B	0.15518	17.1	0.0483840
A	0.06805	7.49	0.0219040

Figure 9: Sensitivity to findings report for query node C of Figure 5.

All variables for which the sensitivity analysis is performed are listed according to their influence. The higher the mutual information value, the higher is the influence of the variable on the query node. For example, the sensitivity to findings report of node C of Figure 5 reveals that node B has a higher influence on the query node than node A. In contrast, if the "Mutual Info" values of two variables are 0, the variables are mutually independent or *d*-separated (see Chapter 2.4.1).

[6] Netica ► Network ► Sensitivity to findings.
[7] Netica's Help System ► Special Topics ► Sensitivity Analysis ► Sensitivity-Example.

2.4.3. Sensitivity to parameters

To test how sensitive a query node is to changes in other parameters, the CPTs of the other nodes can be incrementally changed one after the other, e.g. the probability of a node with two states can be changed step-wise from 100:0 to 80:20 to 60:40 to 40:60 to 20:80 and 0:100 to test how the probability distribution of the query node changes. This straightforward variation of CPTs takes a lot of time. Therefore, Coupé and van der Gaag (2002) introduced a more efficient method that restricts the sensitivity analysis to those variables of which the query node is algebraically dependent. This way, they identify a so-called *sensitivity set* of variables with the highest influence on the query node. With a certain algorithm, *sensitivity functions* are determined for each parameter in the sensitivity set (Korb and Nicholson, 2011: 391ff.). With these sensitivity functions, coefficients can be calculated. Parameter changes can thus be illustrated as linear sensitivity functions if there are no child nodes and as hyperbolic sensitivity functions if there are child nodes (Pollino and Henderson, 2010).

Due to the high number of deterministic CPTs, this kind of sensitivity analysis is not performed for the BNs presented in this thesis. A step-by-step description of sensitivity to parameters analysis can be found in the Master thesis of Hansson and Sjökvist (2013: 25–36).

2.5. Bayesian Network types

2.5.1. Bayesian Decision Networks

Bayesian Decision Networks (BDNs) are applied in cost-benefit-analyses. BDNs are BNs with so-called decision nodes and utility nodes. In Netica, decision nodes are depicted as blue rectangles; utility nodes are depicted as red diamonds. The states of the decision node usually represent management options. A BDN can be used to identify the management option with the highest benefit at lowest cost. Costs and benefits of management options are quantified with the help of utility tables. Each utility node has an attached utility table. In utility tables, costs are expressed in numerical values between -1 and 0; benefits are expressed in numerical values between 0 and +1 (Figure 10).

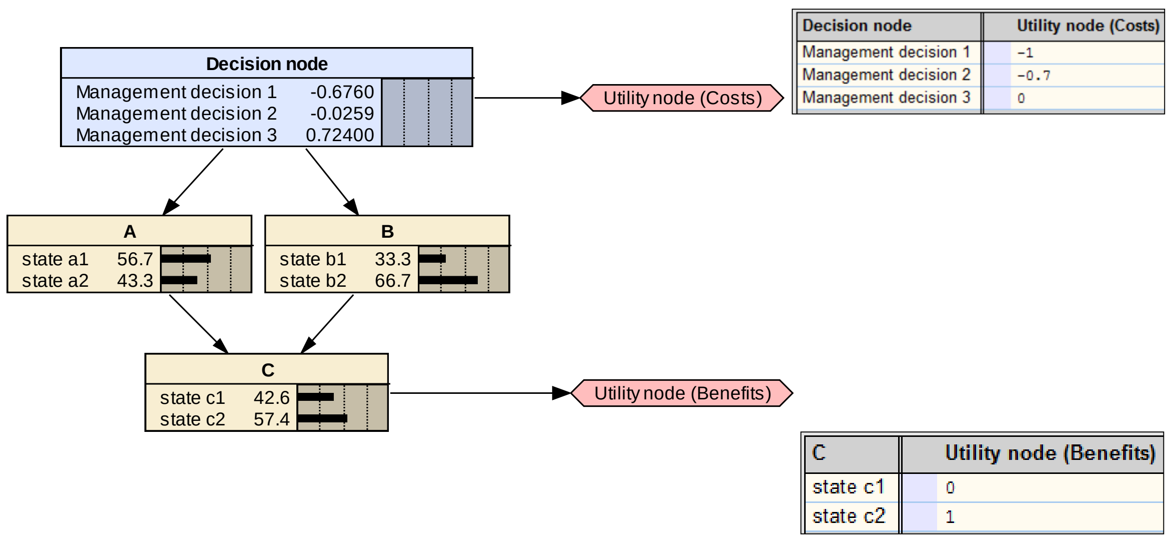


Figure 10: Bayesian Decision Network with three nature nodes (A, B, C), one decision node, two utility nodes and their associated utility tables.

Netica calculates the total expected utility (EU) or net benefit of each state of the decision node by subtracting the product of utility and probability of each state (between 0 and 1) from the standardized cost of each state (between 0 and -1) (5) (adapted from Jensen and Nielsen, 2007: 283):

$$\mathrm{EU\ (Mgmt\ 1)} = \mathrm{Costs\ (Mgmt\ 1)} + \sum_{\mathrm{C}} \mathrm{Utility(C)} * \mathrm{Probability\ (C|Mgmt\ 1)} \qquad (5)$$

The total expected utility shown behind each management decision can range between -1 and 1. Negative values (-1 to 0) indicate that costs outweigh the benefits; positive values (0 to +1) indicate that benefits outweigh the costs. In the example BDN, management decision 3 has the highest total expected utility (Table 9).

Table 9: Calculation of total expected utilities (EU) for each state of the decision node of Figure 10.

State of decision node	Costs	Utility (U) of C		Probability (P) of C[8]|Mgmt decision		U(C) * P (C|Mgmt decision)		∑ (U (C)*P (C|Mgmt decision))	EU = Costs + ∑ (U(C) * P (C|Mgmt decision))
		c1	c2	c1	c2	c1	c2		
Mgmt decision 1	-1	0	1	0.676	0.324	0	0.324	0.324	-0.676
Mgmt decision 2	-0.7	0	1	0.326	0.674	0	0.674	0.674	-0.0259
Mgmt decision 3	0	0	1	0.276	0.724	0	0.724	0.724	0.724

[8] Calculated by Netica; these probabilities can be reproduced by setting the probability of each management decision to 100% (one by one).

2.5.2. Object-Oriented Bayesian Networks

An Object-Oriented Bayesian Network (OOBNs) consists of several network fragments (framed in Figure 11). These repetitive network fragments are referred to as *classes*. The example OOBN in Figure 11 has four identical classes which can be run with four different sets of values. Using the terms of object-oriented modeling, the model can be *instantiated* or realized four times. Classes that have been instantiated are referred to as *objects* (Jensen and Nielsen, 2007: 84ff.). Here, X serves as input and D and E as output attributes of the four objects. The possibility to aggregate outputs of different classes allows the integration of different scales in OOBNs, e.g. Carmona et al. (2011a) developed an OOBN to compare different farm types within the same model.

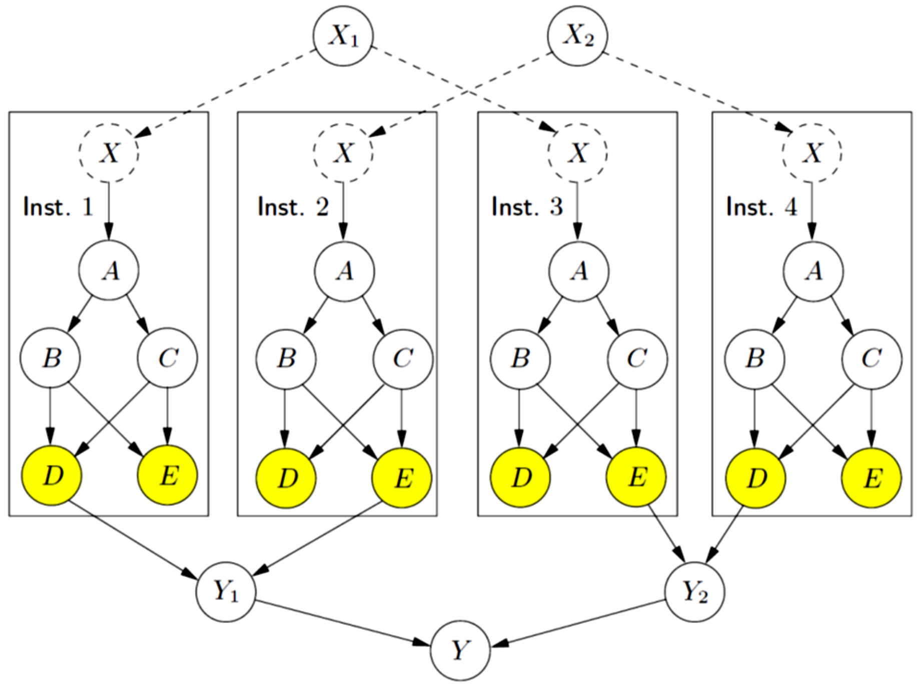


Figure 11: General structure of an Object-Oriented Bayesian Network. (Jensen and Nielsen, 2007: 86).

2.5.3. Dynamic Bayesian Networks

A Dynamic Bayesian Network (DBN) consists of local models with identical network structures and conditional probabilities for different points in time (Jensen and Nielsen, 2007: 91ff.). The time steps are referred to as time slices. The causal relationships within a time slice are represented by *intra-slice arcs*; the relationships between the variables at different time steps are represented by *inter-slice arcs* (Figure 12) or *temporal links* (Korb and Nicholson, 2011: 112ff.). Figure 12 shows how four connected local models. The variables in each time slice are influenced by its parent nodes (intra-slice arcs) and by their counterparts from the previous time slice (inter-slice arcs). DBNs are used to model change in all variables over time.

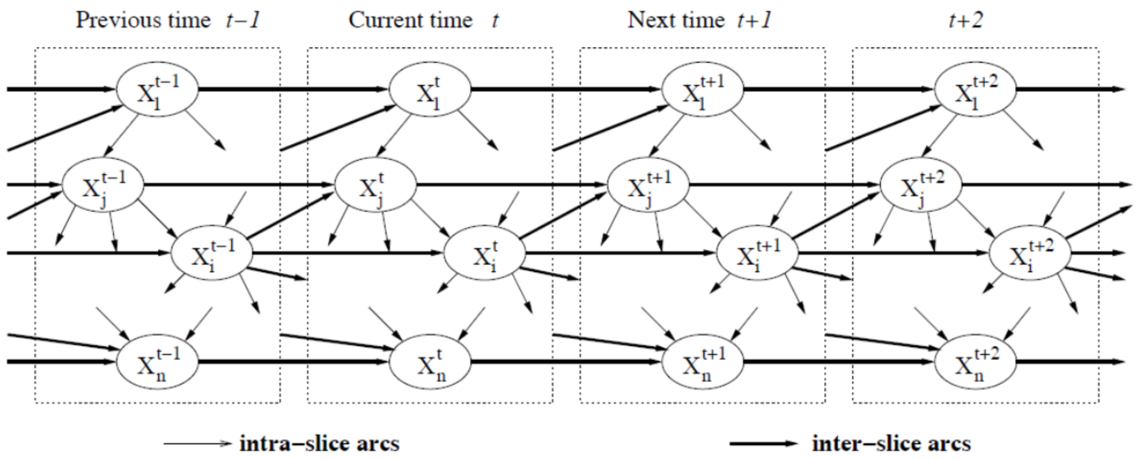


Figure 12: General structure of a Dynamic Bayesian Network. (Korb and Nicholson, 2011: 114).

3. Expert-based Bayesian Network modeling

A literature search within the Institute for Scientific Information (ISI) Web of Science™ Core Collection resulted in 25,150 publications on the topics “Bayesian Network” or “Bayesian Belief Network” from 2003 to 2013. These results were refined by selecting the following seven research fields only: Agriculture, Biodiversity Conservation, Environmental Sciences/Ecology, Fisheries, Forestry, Marine Freshwater Biology, and Water Resources. This led to 1,000 results.

Within these publications, three key word searches were conducted one after the other: (1) “Expert” (131 results), (2) “Participatory” (42 results), and (3) “Stakeholder” (76 results). Without duplicates, this led to 180 results which were screened for Bayesian Network (BN) modeling. Of 146 papers describing BN applications, 80 publications mention that expert knowledge was used for model parameterization. In a last step, the number of publications was reduced (1) by excluding papers which solely mention the use of expert knowledge without providing further information on the expert elicitation process and (2) by selecting only one of several publications describing the same case studies (e.g. (Carmona et al., 2011a; Carmona et al., 2011b, 2013). This resulted in a final set of 50 case studies (see Table A - 1 in Appendix A).

This chapter presents the results of the literature review on how BN models are developed and parameterized with experts. It synthesizes how experts are consulted to develop the network structure and to provide their estimates (Chapter 3.1), it provides an overview of established elicitation formats (Chapter 3.2), and summarizes how expert knowledge is combined – or not combined – within the 50 case studies (Chapter 3.3)

3.1. Consultation format

Within the case studies, the consultation format ranges from sending out questionnaires to individual meetings and group meetings. All these consultation formats have their advantages and disadvantages. Whereas filling in questionnaires requires the least time from the experts, it also provides the lowest opportunity for learning for them. Individual meetings, such as interviews, offer the possibility to provide further information and clarifications during the elicitation. In addition, with individual meetings it is not necessary to find a time and place to assemble all experts in one place. However, discussions and exchange of knowledge during interviews is very limited. Group meetings, such as small group meetings or structured workshops, provide platforms for group discussions which presumably improve the “performance” of the experts (Burgman, 2005). However, if a group discussion is not mastered well by the moderator, some experts dominate the discussion while others keep silent.

The consultation format as well as the number of experts and stakeholders involved changes during the modeling process. At an early modeling stage, group meetings are used to jointly develop the network structure, henceforth referred to as *directed acyclic graph* (DAG) (Figure 13). At a later stage conditional probability values are mainly elicited during individual meetings (Figure 14) and only from a smaller sub-group (e.g. Chan et al., 2010; Schmitt and Brugere, 2013).

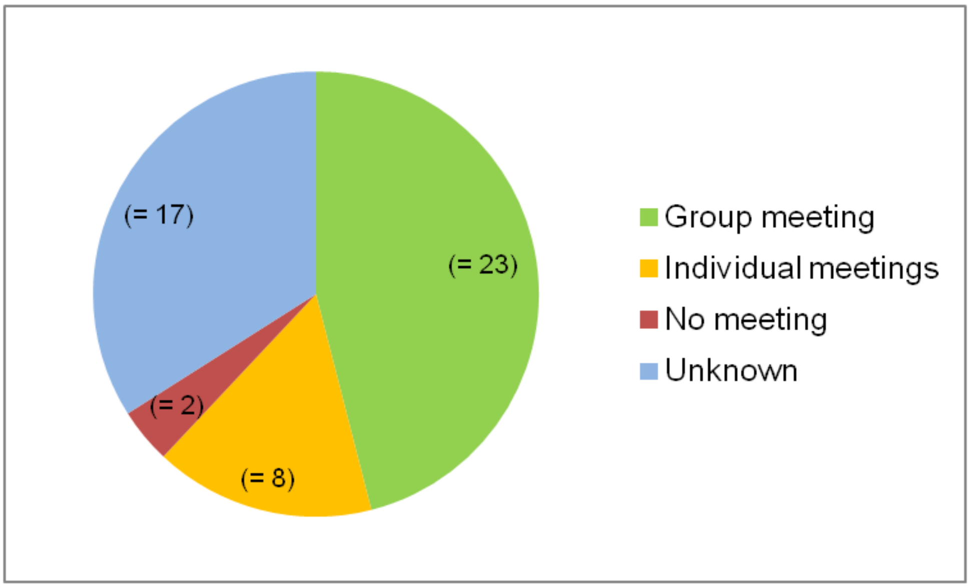


Figure 13: Use of different consultation formats for the development of the network structure in 50 case studies

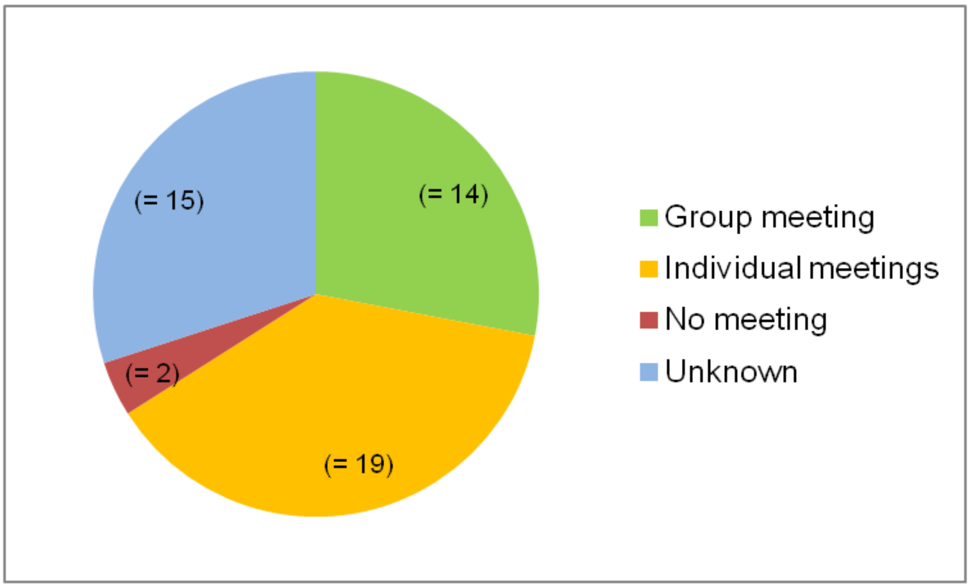


Figure 14: Use of different consultation formats for the elicitation of probability values in 50 case studies.

In some case studies, group meetings are chosen to provide a platform for discussion and convergence among different conflicting stakeholder groups. For example, with a first round of separate group meetings before the stakeholder groups encounter each other in a joint group meeting (Carmona et al., 2013; Chan et al., 2010).

Some case studies attempted to combine the advantages of individual and group meetings. Haapasaari et al. (2013) conducted six individual BN modeling workshops and invited all stakeholders and experts involved to a final joint meeting 1.5 years after the consultations. This way, the stakeholders and experts benefitted from a one-to-one assistance during all modeling steps and still had the possibility to exchange and learn in a group. Baynes et al. (2011) employed a one-to-one ratio of assistants to participants in a workshop setting (14:14). This enables group discussions and networking opportunities while the elicitation benefits from individual assistance.

In only four case studies did experts and stakeholders receive a questionnaire by email. Two of these case studies used this format at a very early modeling stage to ask for feedback on a preliminary network structure, henceforth referred to as *directed acyclic graph* (DAG) (Schmitt and Brugere, 2013; Smith et al., 2007). The other two case studies used questionnaires to populate the conditional probability tables. This was only possible because the BNs consisted of two and five nodes and therefore allowed the elicitation of experts' estimates and stakeholders' preferences with very simple elicitation formats, e.g. on a scale of -2 to 2 (Haapasaari and Karjalainen, 2010; Newton et al., 2007).

3.2. Elicitation format

In the case studies, the network structure and experts' estimates for probability tables (PTs) and conditional probability tables (CPTs) was mainly elicited on paper. Only two case studies mentioned the use of software products (Cmap and Vensim) for the development of conceptual maps or models (Catenacci and Giupponi, 2013; Richards et al., 2013) and none used elicitation software tools to retrieve experts' probabilities (as introduced by Low-Choy et al., 2012).

The 50 case studies exhibited a variety of elicitation formats for the parameterization of BNs (Figure 15). In 35 case studies, experts' estimates were elicited in the form of (conditional) probability values – either with empty (conditional) probability tables (32 cases) or with the help of probability scales (3 cases). In the other case studies, experts' estimates were elicited as weights (3 cases), in a frequency context (3 cases), as rankings (2 cases) or in other formats – ranging from quantile elicitation (Allan et al., 2012), graphical elicitation of bars in a coordinate system (Vilizzi et al., 2012) to the elicitation of triangular fuzzy numbers (Ren et al., 2008).

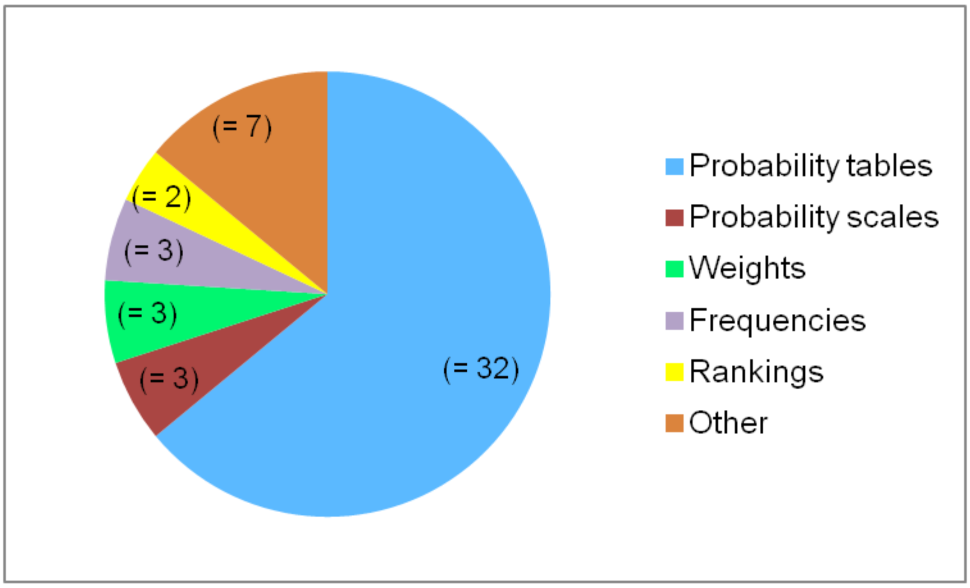


Figure 15: Use of different elicitation formats for the derivation of probability values in 50 case studies.

Some case studies used standardized probability scales as elicitation format (Jensen et al., 2009; Penman et al., 2011; Pike, 2004). On these scales, point probabilities or probability intervals are expressed in both numerical values and related verbal expressions ("verbal anchors"), such as "impossible" for 0.0 and "certain" for 1.0. These three case studies used probability scales introduced by Renooij and Witteman (1999), van der Gaag et al. (2002), and Pollack (2003) as cited in Penman et al. (2011). Another transformation table between probability intervals and verbal expressions of uncertainty can be found in the work of Druzdzel (1996).

In three case studies, experts were asked to estimate weights for each parent node in percent (Baran et al., 2006; Baynes et al., 2011; Holzkämper et al., 2012; Kumar et al., 2012). These weights are used to represent how much influence each parent node exerts on the child node. To calculate the conditional probability tables (CPTs) of the whole network, it is necessary to elicit the unconditional probability values for the root nodes and the weights of influence for all parent nodes, including the root nodes. Two of these case studies used a modified version of the weighted sum algorithm introduced by Das (2004). In three case studies, probability values were derived from elicited frequencies (Borsuk et al., 2001; Florin et al., 2013; Money et al., 2012). Example questions for the elicitation of frequencies can be found in the Appendix (Table A - 1). In two case studies, experts were asked to rank all combinations of states of the parent nodes from greatest positive to greatest negative effect on the child node (McDowell et al., 2009; Nash et al., 2010). In a second step, the modelers assigned probability values based on these rankings and information from scientific literature.

Independent from the elicitation format, there are two approaches to ease the expert elicitation. One approach is to reduce the number of values to be elicited, e.g. by using the structured elicitation technique devised by Cain (2001), also referred to as the "CPT calculator" (Bashari et al., 2009). In a nutshell, this method requires the elicitation of probability values for the worst-case scenario, the best-case-scenario and for the scenario in which all states of the parent nodes are "preferable" except for one. Cain (2001) introduced a method to calculate so-called "interpolation factors" based on these elicited probability values – for different variations of BNs, e.g. with varying numbers of states and parent nodes. In a second step, the missing probability values can be calculated using the interpolation factors (Cain, 2001: Appendix 2). Eight case studies applied this method to elicit the probability values or frequencies for a reduced number of scenarios (Bashari et al., 2009; Baynes et al., 2011; Florin et al., 2013; McDowell et al., 2009; Nash et al., 2010; Smith et al., 2012; Smith et al., 2007; Wang et al., 2009a).

The other approach is to simplify CPTs by assuming independence of causal influence (ICI) among several parent nodes. The advantage of assuming independence of parent nodes is that the number of parameters to be elicited does not grow exponentially but linearly with the number of parent nodes. This way, an expert does not have to formulate conditional probability values for all combinations of parent states but only for the states of each parent node separately. This way, two case studies applied so-called Noisy-MAX distributions, Noisy-AND and Noisy-OR approximations to complex CPTs (Money et al., 2012; Nolivos et al., 2011).

3.3. Combination of expert knowledge

In most case studies, the network structures (DAGs) were developed during group meetings (see Figure 13). When several experts jointly select and link variables, there is no need to combine several DAGs afterwards. Only in few case studies were BN components developed by different groups and merged afterwards (e.g. Money et al., 2012) or developed individually and later combined into a final DAG (Kumar et al., 2012). In contrast, Pike (2004) explicitly did not combine DAGs but developed 10 individual BNs instead.

Only 20 case studies disclosed whether or not expert estimates – that were elicited from more than one expert – were averaged. In fourteen case studies, probability values that were elicited from different groups or individuals were averaged (see Table A - 1). In most cases, expert estimates were treated equally and therefore unweighted averages were calculated. In three case studies, experts and stakeholders discussed the probability values until group consensus was reached (Baran et al., 2006; Hamilton et al., 2007; Murray et al., 2012). Only in three case studies were probability values explicitly not averaged (Pike, 2004; Richards et al., 2013; Tiller et al., 2013). Whereas Pike developed 10 different BNs, Richards et al. (2013) and Tiller et al. (2013) represented the expert estimates in one BN with the help of a conditioning or auxiliary variable (Kjaerulff and Madsen, 2008: 199ff.). Each state of the auxiliary variable represents an expert and by selecting a certain "expert" state, the BN software shows the probability distributions based on his or her estimates.

4. Case Study Northwest China: Ecosystem services of urban and peri-urban vegetation in oasis towns in Xinjiang

4.1. Introduction

This case study was conducted in Xinjiang Uighur Autonomous Region in Northwest China. With an area of 1.6 million km², Xinjiang constitutes the largest administrative division of the People's Republic of China. The "Sustainable Management of River Oasis along the Tarim River, China" (SuMaRiO) project aims at contributing to sustainable land and water management in the Tarim Basin in Southern Xinjiang. The Tarim (in Pinyin[9] "Talimu") Basin is encircled by the Tian Shan mountain range in the North and the Kunlun Shan mountain range in the South and encompasses the Taklamakan Desert, the second largest sand desert in the world (Figure 16).

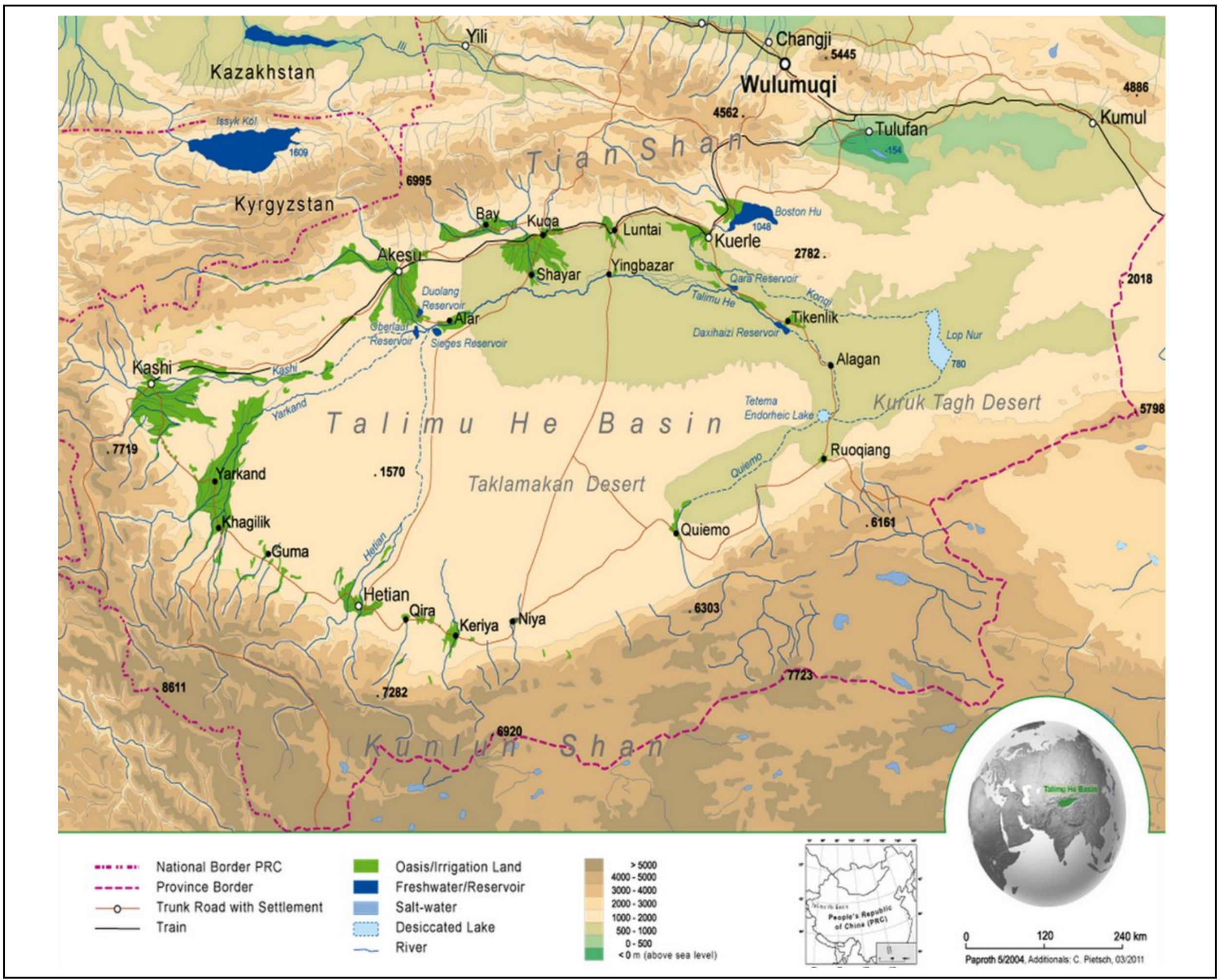


Figure 16: Map of the Tarim Basin (Paproth, 2004, modified by Pietsch, 2011). The map was provided by the Institute of Applied Physical Geography of the Catholic University of Eichstätt-Ingolstadt.

[9] Pinyin is the official phonetic transcription system to transfer the pronunciation of (Mandarin) Chinese characters into the Latin alphabet.

This case study focuses on ecosystem services provided by urban and peri-urban vegetation of oasis towns at the margin of the Taklamakan desert. Expert interviews and workshops were conducted in the two case study towns Aksu (in Pinyin “Akesu”) and Korla (in Pinyin “Kuerle”) as well as in Urumqi (in Pinyin “Wulumuqi”) which is the capital of Xinjiang (Figure 16).

Doing research at the natural and social science interface in China often holds unexpected intricacies (Van Den Hoek et al., 2012). This chapter therefore highlights which particular challenges the project team[10] faced while conducting the case study in Xinjiang from 2011 to 2014 (Chapter 4.1.1) and describes how the research conditions affected the design of the BN modeling process (Chapter 4.1.2).

4.1.1. Research conditions in the case study region

The entry requirements and regulations for conducting expert interviews and workshops (WS) in Southern Xinjiang are strict, especially for foreign researchers in positions below professorship. Although this case study did not touch sensitive issues, such as the treatment of ethnic minorities, to receive formal invitations for business visa, detailed itineraries needed to be submitted three months in advance of each field trip. These itineraries had to give a detailed overview of all planned research activities, such as WS program, list of WS participants, as well as the work plan for each day of the field trip, incl. names of foreseen interview partners. Each invitation was issued for two-week stays only.

The requirements and regulations for doing research in Aksu were stricter than for Korla. This could be related to different levels of prosperity, composition of ethnicity, and proximity to “hotspots” of violence between police forces and ethnic minorities. Aksu has a higher population and a lower per capita gross regional product compared to Korla (Jin, 2010) which experienced an oil boom as the location of the Petro China Tarim Basin Oil Control Center. Aksu has a slightly larger proportion of ethnic minorities compared to Korla which experienced a higher in-migration of Han Chinese due to the oil boom. As Aksu lies in the vicinity of Kashgar, it was chosen as the base for China’s elite anti-terrorist unit – the Snow Leopard Commando – following the violent incidents in Kashgar and Hotan in July 2011 (China Digital Times, 2011). In retrospect, the initial focus on Aksu as a case study town might have complicated the issuance of formal invitations.

[10] Referring to the SuMaRiO team at Goethe University Frankfurt, cooperating sub-projects from other German universities, and local partners in Xinjiang.

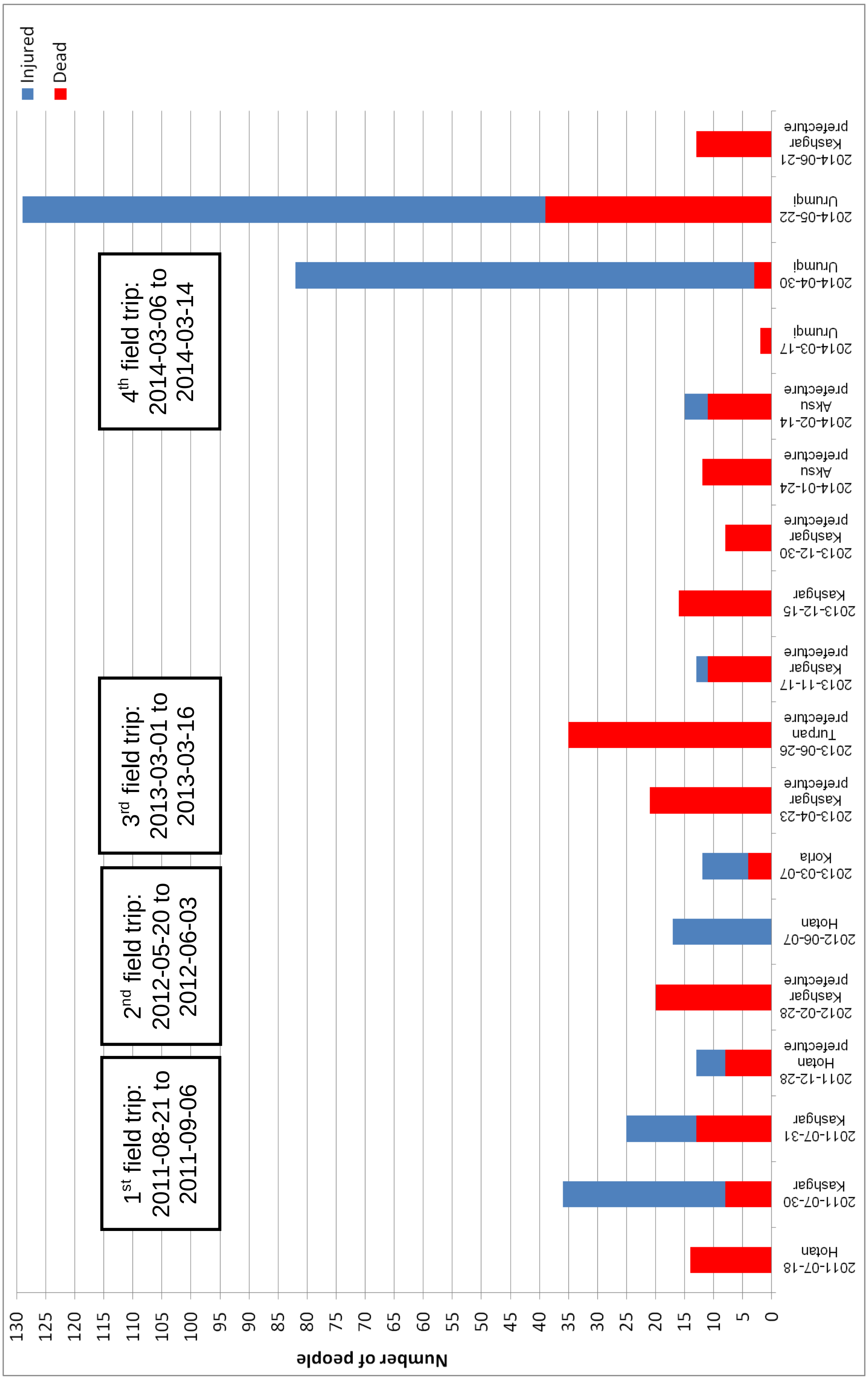


Figure 17: Timeline of field trips and violent incidents in Xinjiang, 2011-07 – 2014-06 (see Table F - 1 for references).

These stricter regulations for Aksu and social unrest in Southern Xinjiang affected the design of the modeling process as well as itineraries, especially if incidents happened shortly before or during the field trips (Figure 17). For the first field trip, Hotan and Kashgar needed to be canceled from the route. During the second field trip, the venue of WS 1 needed to be changed from Aksu to Urumqi – only five days before the workshop date. During the third field trip, two experts from Aksu could not attend WS 2 in Korla after it had to be postponed from Sunday morning to the afternoon. The participants from Aksu gave two reasons for their cancellation. First, the postponement precluded their return trip by car on the same day. Second, they were reluctant to come due to the violent incident in Korla on 7th March 2013 (Figure 17) and also due to uncertainty about the local situation.

Despite strict regulations, experts from Aksu and Korla were involved in the modeling process. This was only possible with the support of engaged local partners with well-functioning professional networks in Southern Xinjiang. All interviews and workshops needed to be conducted in Mandarin. The author’s ability to speak a little Mandarin served as an ice-breaker at the very beginning of each workshop. Local PhD students supported the WS organizing team with the translation of presentations, questionnaires, and discussions throughout the workshop series.

4.1.2. Design of Bayesian Network modeling process

The Bayesian Network (BN) modeling process started in 2011 with first expert interviews in Xinjiang and Beijing (Table 10). The interviews in Aksu and Korla aimed at establishing contacts for the workshop series and at specifying the model purpose according to the demands of local planners. Most interview partners were experts in the fields of forestry and urban landscape planning. The idea was to involve experts working outside academia to increase the chances that model results would be put into use after the end of the research project. In this chapter, the term “experts working in academia” refers to scientific staff from universities and research institutes. The term “experts working outside academia” refers to managers and planners with specialized knowledge in the respective field, e.g. urban landscape planning and forestry management.

The modeling process was designed for three expert workshops. The initial plan was to use the first workshop for developing the network structure, the second for filling in conditional probability tables (CPTs), and the third for evaluating both the final model and the participatory modeling process. When the duration of each workshop had to be shortened to only three hours due to time constraints of the participants, the methods for each modeling step had to be modified. During WS 1, participants discussed two preliminary BNs which had been developed based on scientific literature instead of jointly drawing causal networks from the scratch. During WS 2, experts' estimates were not elicited in the form of "complicated" CPTs but in other forms. During WS 3, participants applied the final BN and evaluated the method in general instead of evaluating the final BN and the modeling process.

Table 10: Overview of interviewees in Xinjiang and Beijing, 2011 and 2012.

Interviews	Interviewees				Total
	Experts working in academia		Experts working outside academia		
	2011	2012	2011	2012	
Aksu			3	3	6
Korla			1		1
Beijing	3				3
Total	3		4	3	10

Due to strict regulations for foreigners (see Chapter 4.1.1), it was impossible to conduct all workshops in one place and with the same group of experts. When WS 1 had to be relocated from Aksu to Urumqi shortly before the workshop date, the composition of WS participants changed thoroughly. The budget available for covering travel expenses of external WS participants was only sufficient to invite two participants from Aksu to Urumqi. This is why most of the 13 participants of WS 1 were experts from Urumqi working in academia (Table 11). To avoid the strict regulations in Aksu, WS 2 was organized in Korla. Two experts from Aksu were invited but could not attend the workshop after it had to be postponed (see Chapter 4.1.1). During WS 2, it was verbally agreed on that the third workshop could be hosted in Korla at one of the participants' institutes. However, WS 3 had to be conducted in Urumqi again. A change of personnel in the management level was the official explanation for this decision. Two workshop participants from WS 2 could not attend WS 3 as they had been sent to the countryside for one year in the course of a governmental campaign to educate the rural population.

Of the 22 experts who attended the workshop series, only 4 experts attended more than one workshop. Three experts attended two workshops and only one expert attended all three workshops. The high fluctuation of WS participants had advantages and disadvantages for modeling process and models. On the one hand, involving experts from Aksu, Korla and Urumqi broadened the scope of knowledge that could be used for the BNs and the higher proportion of participants working in academia might have contributed to the vividness of WS discussions. On the other hand, the WS participants did not develop an "ownership" towards the model or the modeling process.

In addition, involving experts from three different places made it necessary to generalize the BNs. The final BN focuses more broadly on vegetation in oasis towns, such as Aksu and Korla, instead of delivering precise results for either Aksu or Korla. The prevailing data scarcity or the limited access to existing data made this generalization necessary anyway.

Table 11: Number and disciplinary background of workshop participants.

<table>
<tr><td rowspan="3"></td><td rowspan="3">WS date and location</td><td colspan="4">Number and disciplinary background of workshop participants</td><td>Total</td></tr>
<tr><td>Experts working in academia from</td><td colspan="3">Experts working outside academia from</td><td></td></tr>
<tr><td>Urumqi</td><td>Aksu</td><td>Korla</td><td>Urumqi</td><td></td></tr>
<tr><td>WS 1</td><td>2012-05-25, Urumqi</td><td>9</td><td>2</td><td>-</td><td>2</td><td>13</td></tr>
<tr><td></td><td></td><td>– Urban ecology
– Agricultural sciences
– Social sciences
– Forestry sciences</td><td colspan="3">– Urban planning
– Forestry
– Meteorology</td><td></td></tr>
<tr><td>WS 2</td><td>2013-03-10, Korla</td><td>4</td><td>-</td><td>3</td><td>-</td><td>7</td></tr>
<tr><td></td><td></td><td>– Forestry sciences
– Hydrology sciences</td><td colspan="3">– Urban landscape planning
– Natural conservation management</td><td></td></tr>
<tr><td>WS 3</td><td>2014-03-11, Urumqi</td><td>5</td><td>-</td><td>2</td><td>-</td><td>7</td></tr>
<tr><td></td><td></td><td>– Urban ecology
– Forestry sciences
– Hydrology sciences</td><td colspan="3">– Urban landscape planning</td><td></td></tr>
</table>

4.2. Model development

Local experts from the case study region supported the model development – from discussing the network structure (WS 1) to providing estimates for the model parameterization (WS 2). Due to short WS durations and long time periods between the workshops, not only local experts but also domain experts in Germany and BN experts in Australia contributed to the completion of the final BN. This chapter first depicts how the causal network structure of the BNs changed from 2011 to 2014 (Chapter 4.2.1). Then it summarizes the reasons why broad labels were used as states for the nodes (Chapter 4.2.2) and presents how the final BN was parameterized with the help of expert knowledge and equations (Chapter 4.2.3).

4.2.1. Development of the network structure

As long as BNs are not parameterized, their causal network structure can easily be changed. During 2011-2013, nodes and links were added, deleted and restructured whenever new input could be used from scientific publications, expert interviews, WS discussions, and internal project meetings in Germany. Every change in the network structure was documented and saved as separate Netica file. In chronological order, the network structure was mainly influenced by (1) the literature review before WS 1, (2) discussions during WS 1, (3) the literature review between WS 1 and WS 2, (4) comments during WS 2, (5) an expert interview in Germany, and (6) input from Australian BN modelers.

The initial plan was to develop two BNs: One on “Dust weather management” (Dust BN) and one on “Urban heat stress management” (Heat BN). From October 2011 to October 2013, the Dust BN was developed. The number of nodes varied between 9 and 43; the number of links varied between 9 and 47 (Figure 18). From November 2011 to May 2013, the Heat BN was developed. The number of nodes varied between 15 and 41; the number of links varied between 17 and 45 (Figure 19).

An expert interview in Germany in May 2013 clarified that it was impossible to fill in the CPTs of the Heat BN without data. The work on the Heat BN therefore stopped at the end of May 2013 (Figure 19). In this context, a BN on ecosystem services of urban and peri-urban vegetation (ESS BN) was developed to merge parts of the two BNs (Figure 20). Only the variables related to the provision of shade by urban plants, on which expert knowledge was already elicited during WS 2, were integrated from the Heat BN into the ESS BN. From May to October 2013, the ESS BN included all variables of the Dust BN.

Figure 18: Number of nodes and links of the Dust BN, 2011-10-27 to 2013-10-21. incl. (1) literature review before WS 1, (2) WS 1, (3) preparations for WS 2, (4) WS 2, and (5) simplifications during research stay in Australia.

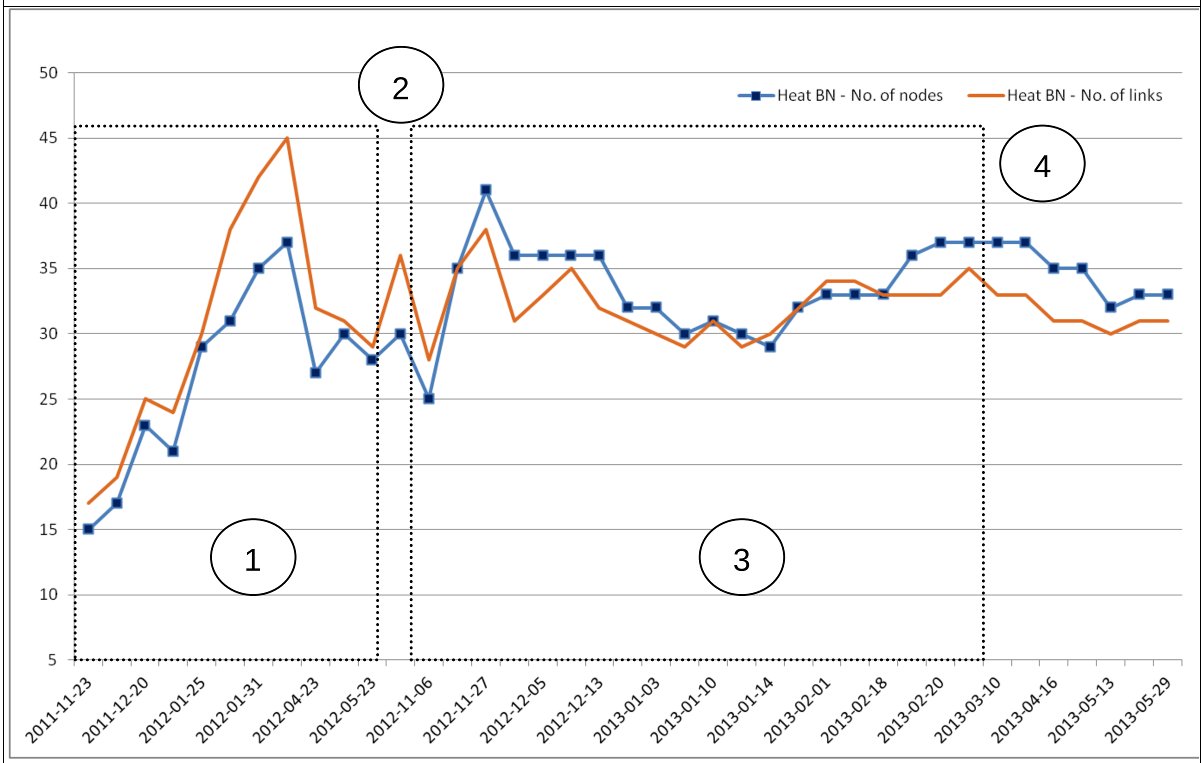


Figure 19: Number of nodes and links of the Heat BN, 2011-11-23 to 2013-05-29. incl. (1) literature review before WS 1, (2) WS 1, (3) preparations for WS 2, and (4) WS 2.

From September to November 2013, the structure of the ESS BN changed again based on the input from Australian experts in BN modeling (Figure 20). Instead of including variables that are difficult to quantify, such as “Peri-urban soil stability” and “Peri-urban wind soil erosion”, the final BN only consists of nodes for which expert estimates were elicited at WS 2 and nodes that could be quantified with equations. The final ESS BN that was presented at WS 3 only consists of 16 nodes and 19 links (see Figure 28).

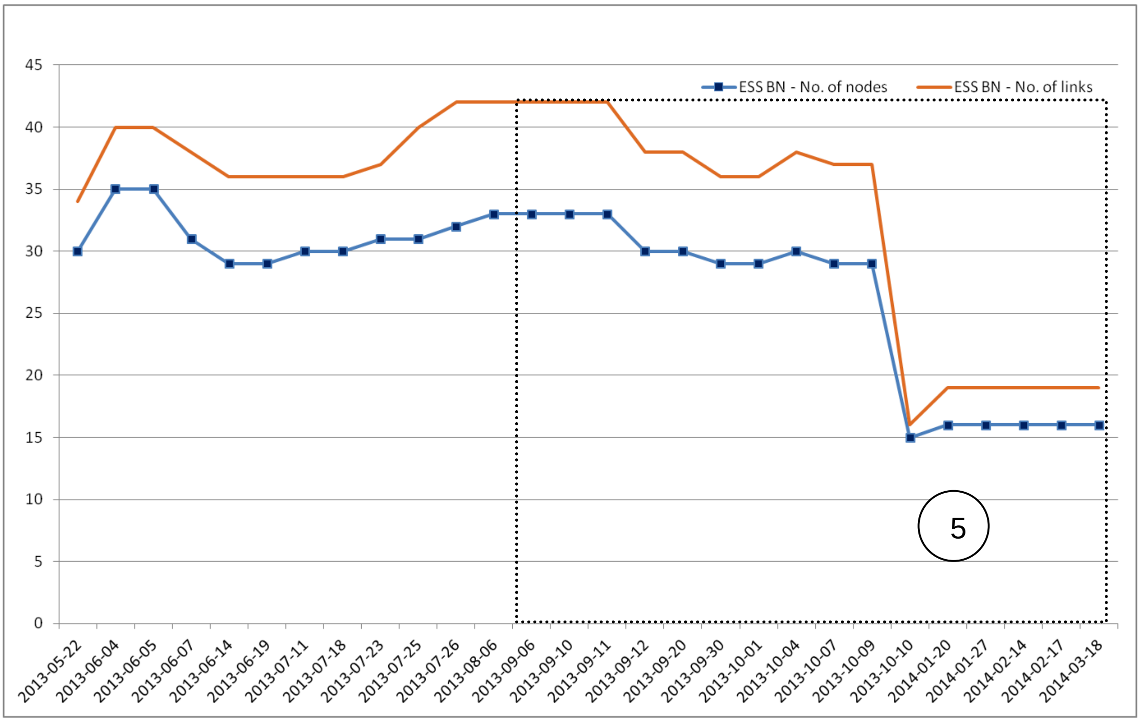


Figure 20: Number of nodes and links of the ESS BN, 2013-05-22 to 2014-03-18. incl. (5) simplifications during research stay in Australia.

4.2.1.1 Preparations for expert workshop 1

To get a first overview on the two problem fields, two preliminary networks had been developed before WS 1. The preliminary Dust BN (Figure 21) consisted of 23 nodes. For the network structure, a review of 20 Chinese publications was undertaken by a project partner. Her translated excerpts were complimented with information from English publications from China (see Table B - 1). The directed links were set according to the causal relationships mentioned in the scientific publications and during the expert interviews in Xinjiang in 2011. In addition, PhD students and postdoctoral researchers of the SuMaRiO project commented on the networks which were presented at the first SuMaRiO PhD seminar in December 2011.

The preliminary Heat BN (Figure 22) consisted of 28 nodes. As local experts were expected to be both more interested and more knowledgeable in the field of dust weather management, more efforts were put into developing a detailed Heat BN. For this, mainly publications on the so-called urban heat island (UHI) effect were used. The UHI effect refers to the phenomenon when the urban air temperature, mostly measured in the urban canopy layer below roof tops, is higher than the air temperature in its surrounding rural areas (Alcoforado and Matzarakis, 2010). In the Heat BN, the UHI effect was equalized with urban heat stress as they share most causes and countermeasures. In both networks “Irrigation needs?” was added as a floating node to get feedback from the WS participants whether or not they were interested to include this node. The final ESS BN includes variables on the irrigation needs of urban and peri-urban plants.

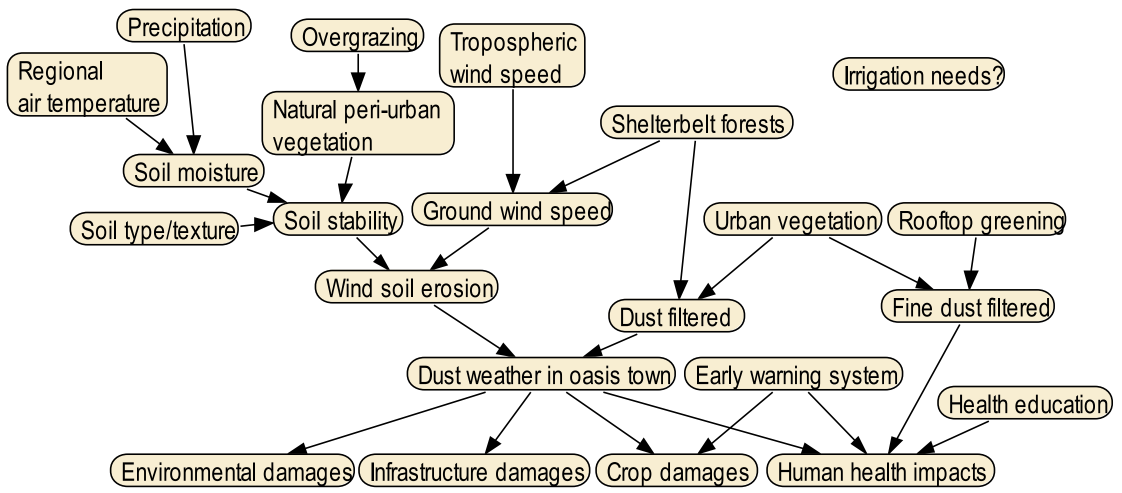


Figure 21: Preliminary Dust BN before WS 1.

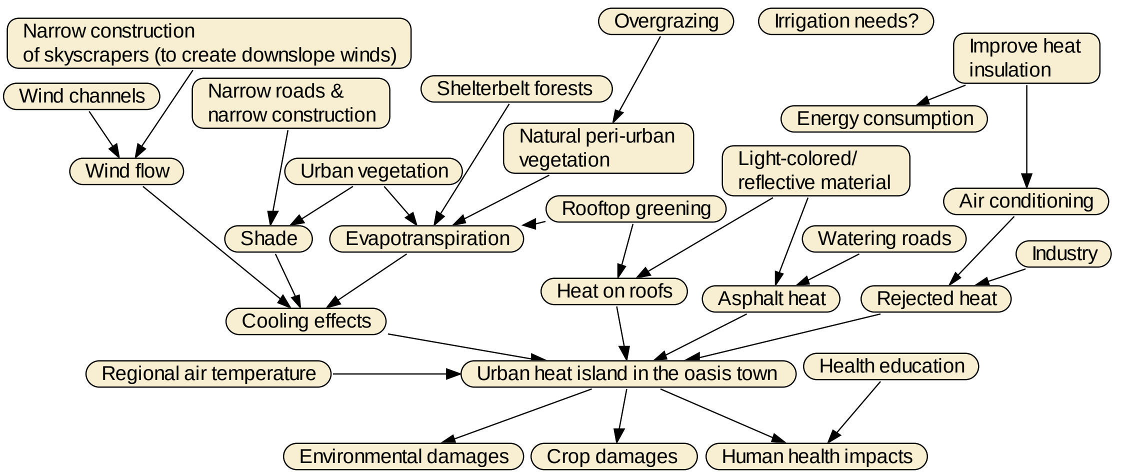


Figure 22: Preliminary Heat BN before WS 1.

4.2.1.2 Expert workshop 1

WS 1 took place in Urumqi on 25th May 2012 and was titled "Sino-German Workshop on Ecosystem Services of Urban and Peri-urban Forests in Oasis Cities of Xinjiang" (see Table C - 1). All WS programmes and evaluations can be found in Appendix C[11]. WS 1 was organized in collaboration with another sub-project of SuMaRiO which also dealt with ecosystem services of urban and peri-urban vegetation. The other sub-project started their WS session in the morning and the BN modeling part was scheduled for the afternoon. The morning session included an introduction to the SuMaRiO project, presentations on urban greening in Xinjiang, the valuation of ESS and two presentations on the history of urban landscape planning in Xinjiang by invited speakers, including a historical review of the Kokyar afforestation project in Aksu. As the problem field of dust weather was already part of the first workshop session, the afternoon session solely encompassed a presentation on urban heat stress management and an introduction into BN modeling. The aim of the afternoon session was to facilitate group discussions to improve the network structures of the preliminary BNs. Before the group discussions started, the network structure of each BN was introduced in detail. The nodes were titled in Chinese characters and the whole network was build-up node by node in front of the participants (Figure 23).

Although the majority preferred to discuss the Dust BN, the 13 participants were

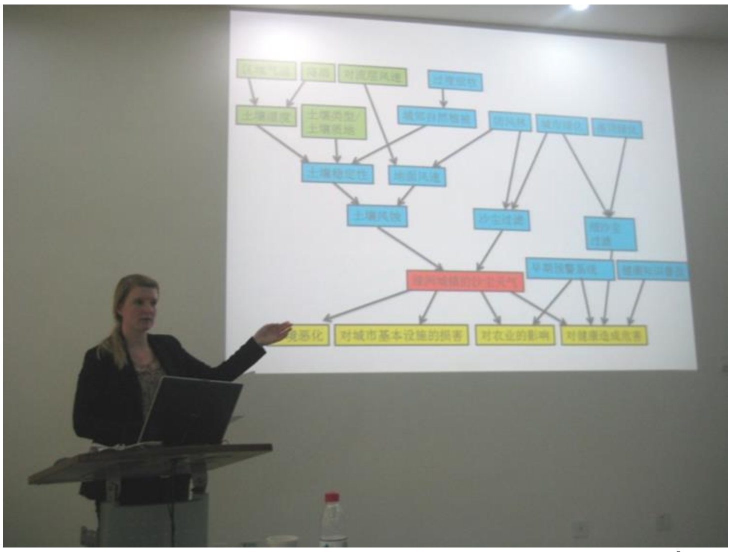


Figure 23: Presentation of Dust BN at WS 1, Urumqi, 25th May 2012.

divided into two groups to discuss the BNs in separate rooms (Table 12). The discussions were facilitated by two moderators – one to interact with the discussants and one to write down the results.

[11] WS programmes in Table C - 1 to Table C - 3; WS evaluations in Figure C - 1 to Figure C - 3.

Table 12: Composition of discussion groups at WS 1.

Discussion group	Experts in discussion groups				No. of discussants
	Experts working in academia	Experts working outside academia			
	Urumqi	Aksu	Korla	Urumqi	
Dust BN	3	2	-	1	6
Heat BN	6	-	-	1	7

After one hour, the results of each discussion were presented to the other group which in turn could comment. The Dust BN discussion group added 18 new nodes to their network (an increase from 23 to 41 nodes) (Figure 24). As the group neither deleted nodes nor re-arranged links, the core network structure of the Dust BN remained exactly the same.

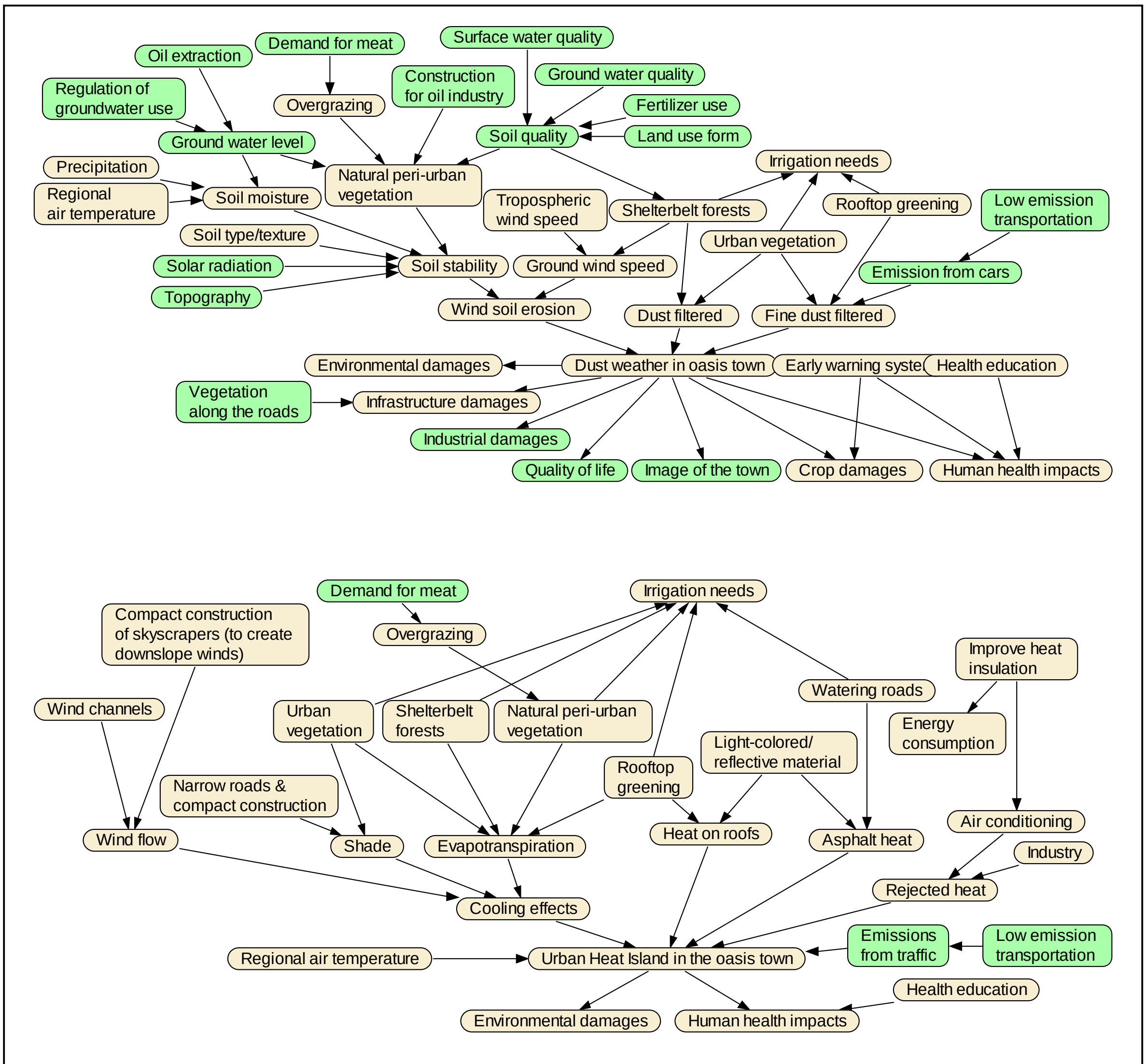


Figure 24: On top, Dust BN after WS 1; at the bottom, Heat BN after WS 1. Newly added nodes are marked in green.

The Heat BN discussion group only deleted the node “Crop damages” and expressed their skepticism towards the node “Narrow roads & compact construction”.This node represented the idea that in narrow roads, buildings can provide shade for pedestrians and adjacent buildings. However, the discussion group noted that this was not realistic for Xinjiang as the volume of individual traffic was increasing and the roads needed to be enlarged. When the Heat BN was presented to the Dust BN discussion group, three nodes from the Dust BN were copied to the Heat BN (in total an increase from 28 to 30; Figure 24). As the complexity of the initial networks as well as the willingness to discuss about these two problem fields was very different, it is difficult to compare the two expert discussions.

4.2.1.3 Preparations for expert workshop 2

Between WS 1 and WS 2, the network structure of both BNs was frequently changed. The number of nodes of the Dust BN varied betwen 23 and 43 (see Figure 18) and the Heat BN consisted of 25 to 41 nodes (see Figure 19). In this time span, 5 Netica files were created for the Dust BN and 20 Netica files were saved for the Heat BN.

Table 13: Number of nodes before and after WS 1 and WS 2.

	No. of nodes before WS 1	No. of nodes after WS 1	No. of nodes of before WS 2	No. of nodes after WS 2
Dust BN	23	41	26	23
Heat BN	28	30	37	37

The number of nodes of the Dust BN was reduced before WS 2 (Table 13). From the 18 newly added nodes, only three nodes remained part of the network structure (Figure 25). Some nodes were deleted because the causal relationship was difficult to quantify, such as the link between “Solar radiation” and “Soil stability”, other nodes were deleted as they went beyond the scope of the BN, such as “Low emission transportation” or “Demand for meat”. The BN presented during WS 2 only had one leaf node (“Human health impacts”) instead of seven. The node “Transportation of dust” was added.

This version of the Dust BN was build as a Bayesian Decision Network (BDN) with “Urban and peri-urban tree species” as decision node, “Irrigation needs” as utility node for costs and “Ecosystem Services” as utility node for benefits (Figure 25). Utility nodes are depicted as red diamonds (see Chapter 2.5.1). As long as BDNs are not parameterized, they can be regarded as causal networks. The red nodes highlighted the two main objectives of the BN, the “Air quality in oasis town” and “Human health impacts”. The yellow nodes represented external factors which could not be influenced by urban landscape planning and management. The green and turquois nodes represented management options of which the turquois nodes had a spatial dimension, e.g. increasing or decreasing extent of peri-urban vegetation.

As the WS discussion on the Heat BN resulted in a few comments only, an extensive literature review was undertaken after WS 1. Scientific publications on the UHI effect revealed many two-directional causal relationships that could not be represented in the Heat BN as BNs allow no feedback loops. Here, three examples are mentioned in which only one of several caualities could be included in the BN. First, the UHI effect or “urban heat dome” can reduce the ventilation and thereby increase air pollution (Alcoforado and Matzarakis, 2010). Other sources highlight that ventilation may also be induced by the UHI itself. The UHI supports the advection of cooler and cleaner air from the outskirts. This phenomenon, also refered to as UHI circulation or country breeze, is supported by natural or artificial ventilation paths. However, the directed links in the Heat BN only indicate that “Ventilation” influences “Air pollution” which influences “Heat storage” which influences the “Urban Heat Island effect” (Figure 25).

Second, the diverging effects of “Ground wind speed” in regions with great diurnal temperature ranges. Pearlmutter et al. (2007) argued that low ground wind speed during day-time can reduce urban heat stress in these regions due to the high thermal inertia of the buildings. In this respect, reducing ground wind speed, e.g. by compact construction or vegetation, had a positive effect. However, reducing ground wind speed also decreases ventilation and thereby increases the amount of pollutants in the air which supports atmospheric heating. As it was impossible to represent both cause-effect-relationships in the Heat BN, only the latter relationship was included.

Third, the challenge of both high diurnal and seasonal air temperature amplitudes in cities in hot arid climates. In order to avoid heat stress during summer, it is necessary to reduce the solar gain or “Heat storage” of cities. This can be achieved by “Urban greening” and “Highly reflective building materials”. The Heat BN solely focuses on these summer conditions and thereby neglects the fact that the solar gain should be maximized in winter (Alcoforado and Matzarakis, 2010). Despite these difficulties with the Heat BN, both BNs were presented at WS 2 in Korla in March 2013.

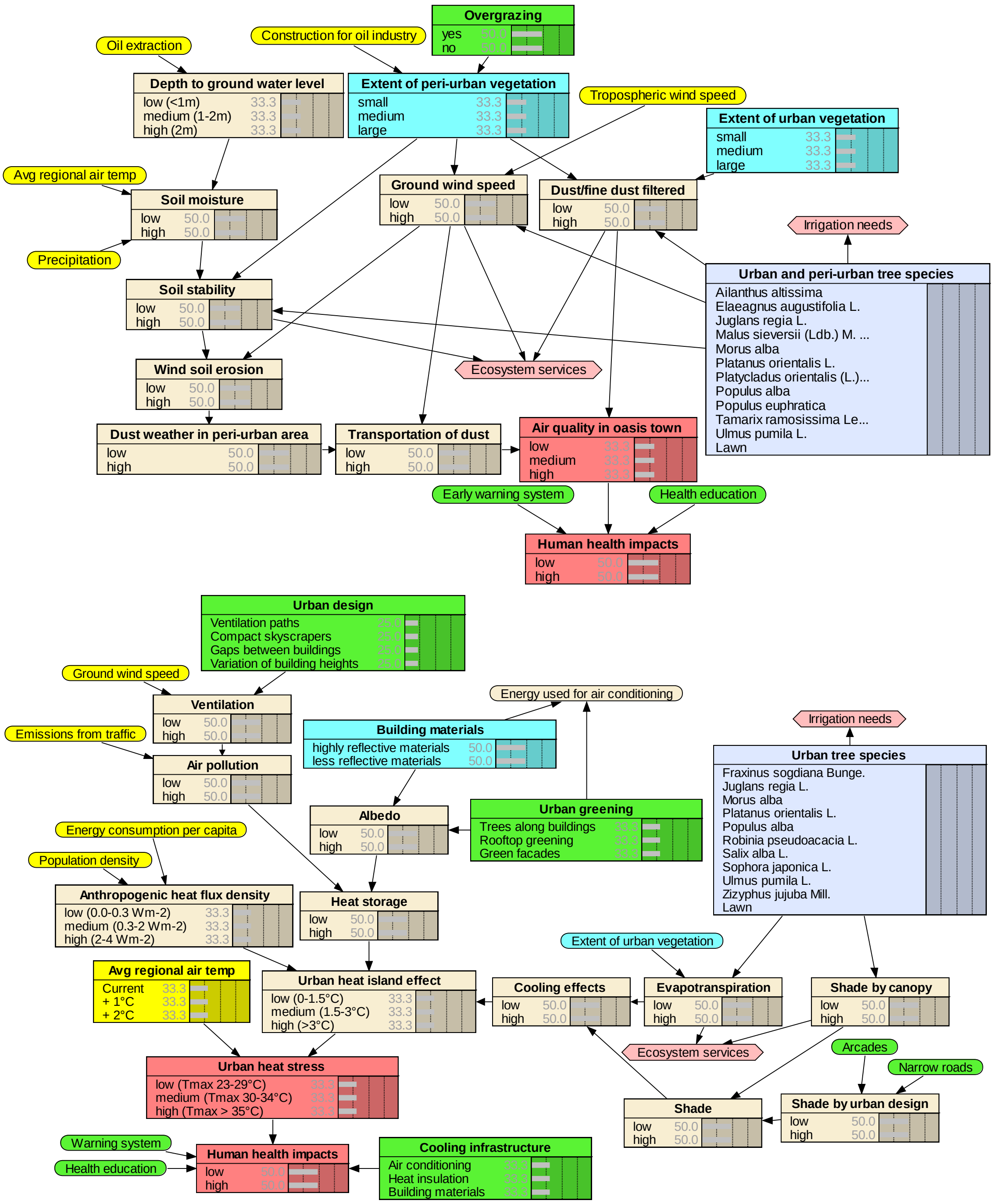


Figure 25: On top, Dust BN before WS 2; at the bottom, Heat BN before WS 2.

4.2.1.4 Expert workshop 2

WS 2 took place in Korla on 10th March 2013 and was titled "Sino-German Workshop on Ecosystem Services of Urban and Peri-urban Forests in Oasis Cities of Xinjiang: The role of forests in relieving dust & urban heat"(see Table C - 2 in Appendix C). The aim of this workshop was to elicit experts' estimates for the generation of CPTs. As only one of the seven WS participants attended WS 1 in Urumqi, the workshop started with presentations on participatory modeling and ESS of urban and peri-urban forests in oasis cities, an introduction into BN modeling, and the presentation of the BNs step-by-step (Figure 26, at the top). Each new node was visualized with photos and figures from research in China and examples from practice in Germany (Figure 26, at the bottom).

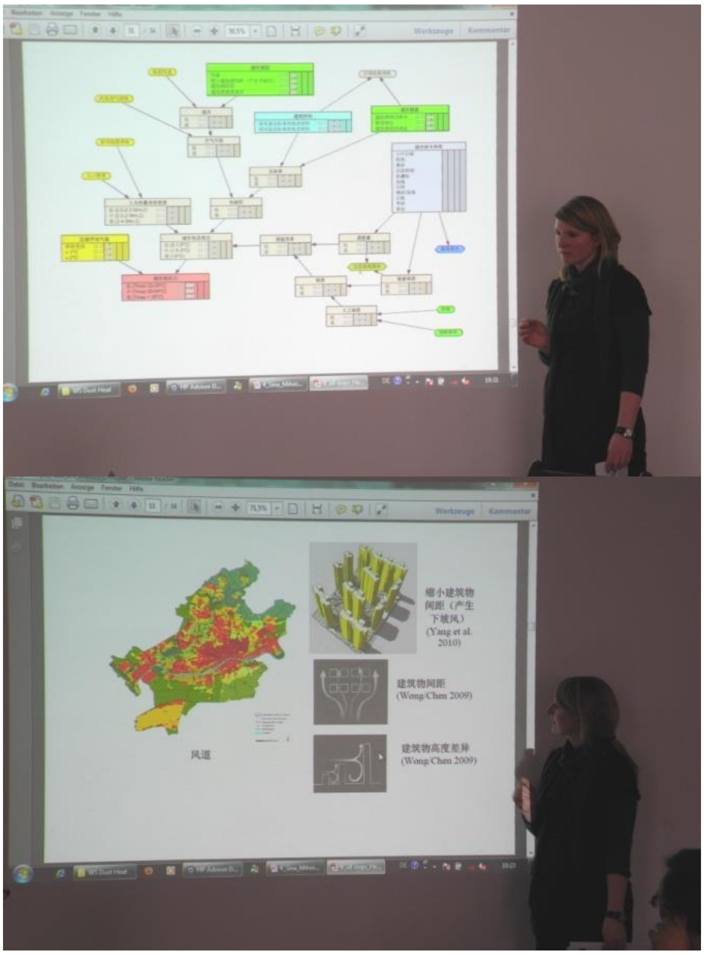


Figure 26: Presentation of Heat BN at WS 2, Korla, 10th March 2013.

When the WS participants were asked for feedback after each BN presentation, they agreed on most of the causal relationships and only had minor changes to the network structure. In the Dust BN, two nodes (“Construction for oil industry” and “Oil extraction”) which were added by participants from Urumqi during WS 1 were deleted. The participants said the oil industry was located in the desert far outside of town and therefore had limited or no influence on vegetation or ground water levels in the peri-urban area. The node “Overgrazing” was deleted after the participants said that this problem had already been solved due to strict regulations in the case study towns. The node “House prize value” was added in the context that peri-urban and especially urban greening increased the value of adjacent houses. The nodes “Extent of urban vegetation” and “Extent of peri-urban vegetation” were merged as the WS participants counted the peri-urban vegetation as urban vegetation. This became apparent when all participants from Korla stated that the urban vegetation in Korla covered 40% of the urban area – this fraction could only be reached if they counted large afforestation projects outside of town, such as the Dong Shan project, into the urban vegetation.

In the Heat BN, the node “Emissions from traffic” was deleted. The node “Shade by urban design” was renamed into “Shade by buildings”. The node “Extent of urban vegetation” was changed into “Urban surface” – a node for which the percentages for the states “Built environment”, “Urban greening”, and “Water bodies” could be distributed according to the respective case study town. The state “Water bodies” was added after a participant highlighted the cooling effect of water bodies in urban spaces. The new node “House price value” was also added to the Heat BN.

4.2.1.5 Expert interview in Germany

After WS 2, most causal relationships in the Heat BN still needed to be quantified. Therefore, an interview with an expert from the field of urban climatology was conducted on 14th May 2013. The expert was not able to fill in the CPTs without data. To estimate conditional probability values, he would have needed at least data on local urban geometry such as heights of buildings and widths of streets and building materials. However, the interview partner made two comments that helped to clarify misunderstandings related to urban heat stress. First, he emphasized the importance of air humidity for humans to actually suffer from urban heat stress. The same temperatures in a dry desert place and in Hong Kong would pose completely different stress levels to humans. Second, he highlighted that adaptation also decreases the likelihood to suffer from urban heat stress. European tourists who visited either that desert place or Hong Kong would experience higher stress levels than locals.

After this expert interview, it was not clear whether the problem field “Urban heat stress” was a problem in the case study region at all. To calculate the urban heat stress level for Korla, the Discomfort Index (DI) was selected. The DI, first proposed by Thom (1959) as cited in Georgi and Dimitriou (2010), has little data requirements compared to more recent indices which at least account for radiation (Epstein and Moran, 2006). Here, the equation to calculate the DI (6) was adopted from Georgi and Dimitriou (2010):

$$DI = TEM - 0.55(1\text{-}0.01\ HUM)\ (Tem\text{-}14.5)°C \qquad (6)$$

with DI being expressed in °C, TEM being the air temperature in °C and HUM being the humidity in percentage.

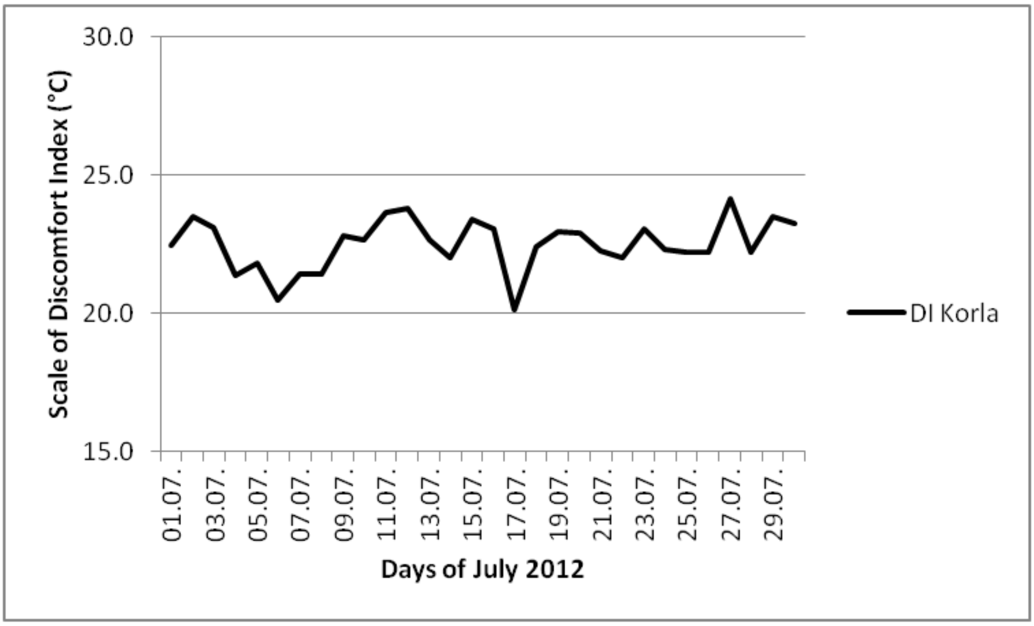


Figure 27: Daily Discomfort Index (DI) values in Korla, July 2012.
DI values were calculated based on daily average temperatures and average humidity in Korla (meteorological station 516560) derived from TuTiempo (2014).

Although in Korla the month July had the highest average humidity and the second-highest average temperature in 2012, the DI never exceeded the threshold of 24°C (Figure 27) above which more than half of the population feels some kind of discomfort (Georgi and Dimitriou, 2010). This does not necessarily mean that there is no urban heat stress in Korla. For this calculation, only daily average temperatures and average humidity data were available (TuTiempo, 2014). With the great diurnal temperature ranges, it is possible that the discomfort in Korla would be much higher if hourly temperatures and humidity data was available. Due to this lack of data, the work on the Heat BN ended shortly after the expert interview (see Figure 19). The nodes “Urban tree species” and “Shading by canopy” were integrated into the new ESS BN which was further developed during a research stay in Australia in 2013.

4.2.1.6 Final network structure

In May 2013, the ESS BN was created with all nodes from the previous Dust BN and two nodes from the previous Heat BN. At the beginning of a three-month research stay in Australia (September-November 2013), the ESS BN consisted of 33 nodes and 42 links (see Figure 20). Experienced BN modelers in Australia suggested to simplify the network and to concentrate on the nodes for which expert estimates had already been elicited during WS 2. Therefore the focus of the BN shifted away from complex causes of dust weather to the basic idea that urban and peri-urban plant species differ in their ability to mitigate dust weather and to provide shade. To simplify the ESS BN, only peri-urban plants influence dust weather mitigation and urban plants solely provide shade. At the end of this research stay, the BN was reduced to 15 nodes and 16 links.

The final version which was presented at WS 3 in March 2014 consists of 16 nodes and 19 links (Figure 28). A full list of nodes and states (Table B - 2) as well as all conditional probability tables can be found in Appendix B[12]. The final BN compares 11 peri-urban plant species in their ability to mitigate dust weather and 10 urban plant species in their ability to provide shade as well as their irrigation needs. It exactly addresses the knowledge gap expressed by local urban landscape planners during an expert interview in August 2011. They explicitly wanted to know which plant species were most effective in mitigating dust weather while needing the least irrigation.

With the root nodes (blue), the model user can compare the effect of single plant species or combinations of plant species on (1) ecosystem services provided by urban and peri-urban vegetation and (2) irrigation needs of urban and peri-urban vegetation. In addition, the extent of the vegetation cover can be increased or decreased in either urban or peri-urban areas or both. The green nodes represent plant-specific characteristics and ecosystem services. The yellow nodes represent irrigation needs of single plant species and the total irrigation need of urban and peri-urban vegetation.

[12] Appendix B provides conditional probability tables that are derived from expert knowledge (Table B - 4 to Table B - 9) and conditional probability tables that are built from equations (Table B - 10 to Table B - 15).

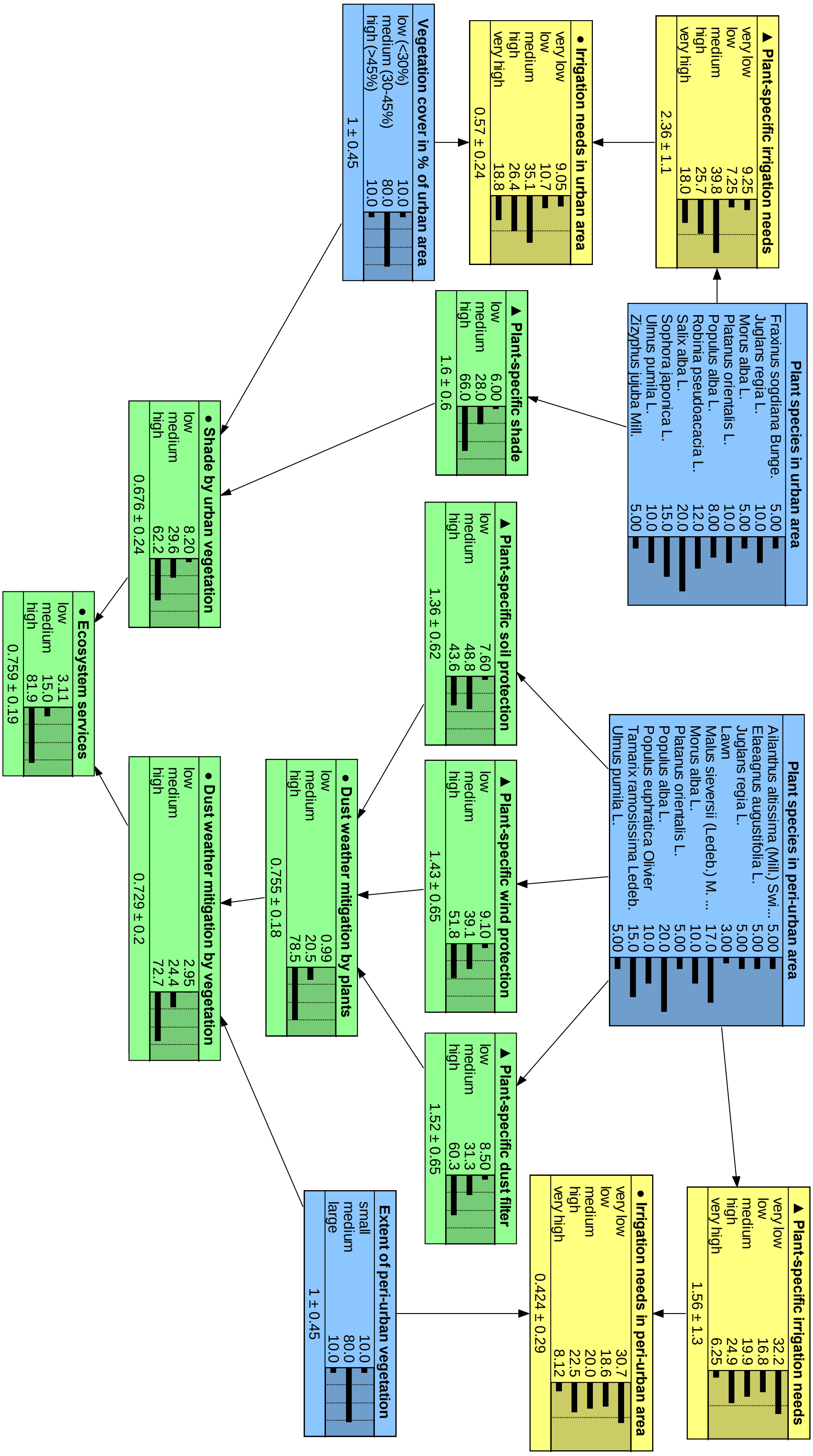


Figure 28: Final ESS BN presented at WS 3.

4.2.2. Definition of states

After the duration of WS 1 was too short to jointly define states, a literature review was conducted to define states based on scientific publications. However, publications use different units to describe the same variables. For example, some publications use air concentration data (in µg/m3) to characterize dust events (Draxler et al., 2001), whereas other publications use horizontal visibility at eye level (<1000m, ≤1000m, ≤10000m) to categorize dust events (Goudie and Middleton, 2006). Even if publications use the same unit, to set realistic classes for the case study region, local data or the support of local experts would have been necessary.

Due to this lack of data, all states of child nodes were expressed with simple labels, such as “low”, “medium”, and “high”. These labels were not defined as most of them were either not measurable (e.g. ecosystem services) or potentially measurable but unknown (e.g. the “Irrigation needs” in m^3). For “Plant-specific irrigation needs” the label “very low” was used for the lowest irrigation need and the label “very high” for the highest irrigation need among the plants species. This way, the BN can be used to compare the plant species with each other.

The states of root nodes can be used to compare management options. The 10 urban and 11 peri-urban plant species used as states of the two root nodes were chosen in cooperation with an expert from the field of urban ecology with long-term working experience in the case study region (Table B - 2). The expert selected plant species that have been increasingly planted in Korla and Aksu and species that are – in his opinion – very suitable to prevent dust weather and to provide shade and therefore should be planted more often in the future. Defining the states for the two root nodes on the extent of vegetation was especially difficult. Some experts counted peri-urban vegetation as part of the urban vegetation and it was impossible to elicit the extent of the peri-urban vegetation in a surface measure such as km^2, ha or mu during WS 2. The solution for both nodes (“Vegetation cover in % of urban area” and “Extent of peri-urban vegetation”) was to anchor the medium state to the current state. Subsequently, “low”/”small” and “high”/”large” represent decrease and increase in urban and peri-urban vegetation.

4.2.3. Model parameterization

The first approach was to parameterize the BNs with statistical data. However, the only data available were prefectural data which were not suitable to represent the situation in the two case study towns. For example, in the Xinjiang Statistical Yearbook the area of key afforestation projects (9-26 林业重点工程造林面积) was only available for the whole Bayangol Mongol Autonomous Prefecture and Aksu Prefecture and not for the towns of Korla and Aksu (Jin, 2010). With no access to the Statistical Yearbooks of the towns Aksu and Korla, the second idea was to use information from scientific publications to populate the CPTs. However, this was impossible as the results of several case studies, e.g. regarding the cooling effects of urban vegetation, varied too much to be used as input data. In addition, results from case studies in Greece, Morocco or Botswana are not easily transferable to the case study region, e.g. the cooling effect of urban lakes in Mexico City (Martínez-Arroyo and Jáuregui, 2000) is not the same as the effect of water bodies in Korla. Therefore, only expert knowledge and equations were used to generate the CPTs. Expert knowledge was used to populate the CPTs of all direct child nodes of “Plant species in urban area” and “Plant species in peri-urban area” (▲) (see Figure 28). The child nodes of these nodes (●) were parameterized with the help of simple equations that equally weighted the incoming parent nodes.

4.2.3.1 Model parameterization with expert knowledge

WS 2 aimed at eliciting the knowledge of local experts. To avoid cognitive difficulties with conditional probabilities and especially to elicit as much expert knowledge as possible in a short period of time, we asked the experts to express their knowledge in the form of ratings and numerical values instead of asking them to fill in CPTs by themselves.

Elicitation of experts’ estimates

After the BNs had been introduced step-by-step and comments on the network structure had been collected, the WS participants sat together for one hour to jointly work on several tasks (see Table 14). For tasks 1 and 2, five experts from the fields of forestry science and urban landscape planning were divided into two groups: Expert group A (3 persons) – a representative of local urban landscape planning, a representative of local conservation management and a forestry scientist working abroad; and Expert group B (2 persons) – a representative of local urban landscape planning and a forestry scientist working in the provincial capital.

The expert groups were well mixed in terms of disciplinary background, work place, and international work experience (Table 15) to enhance discussions between experts with local, provincial or international experiences. The two representatives of the local urban landscape planning were intentionally separated.

Table 14: Overview of tasks used for expert elicitation.

Tasks	Experts involved	Description of the task	Elicitation format
Task 1 (Dust BN)	Expert group A (3 persons), expert group B (2 persons)	Table to differentiate the irrigation needs of 11 peri-urban plant species	Numerical values between 0 and 1
		Table to rate the capacity of 11 peri-urban plant species to protect the soil, to serve as wind break, and to serve as dust filter	Four fixed categories (–,+,++,+++)
Task 2 (Heat BN)	Expert group A (3 persons), expert group B (2 persons)	Table to differentiate the irrigation needs of 10 urban plant species	Numerical values between 0 and 1
		Table to rate the capacity of 10 urban plant species to provide shade	Four fixed categories (–,+,++,+++)
Task 3 (Heat BN)	All 7 WS participants individually	Table to rate the potential of other management options to increase ventilation, to provide shade, and to reduce the human health impact from urban heat stress.	Four fixed categories (–,+,++,+++)
Task 4 (Dust BN)	All 7 WS participants in groups of 2-3	CPTs for the nodes "Wind soil erosion", "Soil stability", "Transportation of dust", "Dust weather in peri-urban area", and "Air quality in oasis town" (Figure 25).	Conditional probability values
		Table to rate the potential of health education, warning systems and different types of cooling infrastructure to reduce the human health impacts from dust weather.	Four fixed categories (–,+,++,+++)

For task 1 and 2, the expert groups were asked to first identify the plants with the lowest (0) and the highest (1) irrigation need. This way, the heuristic procedure of anchoring and adjustment was used because it is easier for experts to have an appropriate starting point to adjust the other estimates accordingly (Morgan and Henrion, 1990; Tversky and Kahneman, 1974). This procedure of anchoring helped the experts to assign values between 0 and 1 for all other plants as they always compared their estimate with the already assigned minimum and maximum. In a second step, the experts evaluated plant species using four fixed categories, with – being the lowest and +++ being the highest category (Table 14). The estimates of all expert groups are summarized in Appendix D (Table D - 1 and Table D - 2).

For tasks 3 and 4, all 7 WS participants were asked to fill in the tables, individually and in groups of 2-3 persons. However, the results of these tasks were not used to derive CPTs for the final ESS BN as they all belonged to nodes of the Dust BN and Heat BN that were not integrated into the ESS BN. In addition, some of the elicited CPTs of task 4 were illogic or incorrect. This might have happened due to an overload of tables or due to oversight by the experts after having filled numerous tables beforehand in a very short time (see “Results” in Table 16).

Table 15: Key characteristics of expert groups A and B, and expert C.

	Disciplinary background	Workplace	Experts working in academia	Experts working outside academia	Size of group
Expert group A	Forestry science	Germany	1		3
	Urban landscape planning	Korla		2	
	Natural conservation management	Korla			
Expert group B	Forestry science	Urumqi	1		2
	Urban landscape planning	Korla		1	
Expert C	Urban ecology	Germany	1		1

Table 16: Key characteristics of the workshop series.

	WS 1 Urumqi, 25th May 2012	WS 2 Korla, 10th March 2013	WS 3 Urumqi, 11th March 2014
Purpose of the workshop	Improvement of network structure	Elicitation of experts' estimates	Application and evaluation of BNs
Number of participants	13	7	7
Duration of workshop	3 hours	3 hours	3 hours
Duration of elicitation	1 hour	1 hour	1.5 hours
Elicitation format	Group discussion in two groups	Discussion in groups of 2-3 experts, jointly filling in tables	Using the final BN in groups of 2-3 experts
Results	Two causal networks	23 values (0-1), 60 ratings (– to +++) from 5 participants; 5 CPTs (44 conditional probability values) from 7 participants	Evaluation of BN method and results for local environmental management

The final BN includes estimates of Expert groups A and B (WS 2) as well as estimates of an expert who could not attend the workshop: Expert C (1 person) – an urban ecology scientist who originally comes from the case study region but works in Germany. To be able to combine the elicited estimates, the expert groups were asked how confident they were in their estimates (Table 17). For the calculation of weighted averages, "very confident" expert estimates were weighted three times; "confident" estimates two times; "rather unconfident" estimates once; and "very unconfident" estimates not at all (see Table D - 3 and Table D - 4 in Appendix D).

Table 17: Confidence of expert groups in their own estimates.
Expert groups could decide whether they were very unconfident (-), rather unconfident (+), rather confident (++), or very confident (+++).

	Expert Group A	Expert Group B	Expert C
Plant-specific irrigation needs (urban and peri-urban)	++	+++	++
Plant-specific shade	++	+++	+++
Plant-specific soil protection	++	+++	++
Plant-specific wind protection	++	+++	+++
Plant-specific dust filter	++	+++	+++

Conversion of experts' estimates into probability values

After WS 2, the elicited values between 0-1 and 0-3 (–, +, ++, +++) needed to get converted into conditional probability values. The first conversion step was to decide on the number of states for the expert-based nodes. For plant-specific irrigation needs, five states were used as the experts could use every numerical value between 0-1 to express their knowledge. For all plant-specific characteristics, three states were used as the experts could only choose from four fixed categories.

The second step was to develop conversion tables that allow the systematic translation of all weighted average values of expert groups A, B, and C into conditional probability values. For this purpose, the range between 0-1 was divided into sub-ranges that equal the five states. With 0 being the lowest and 1 being the highest irrigation need, the sub-ranges represented "very low" (0-0.20), "low" (0.21-0.40), "medium" (0.41-0.60), "high" (0.61-0.80), and "very high" (0.81-1) irrigation needs (Table 18). Each row in a CPT has to sum up to 100%. This is why two probability distributions were defined for each sub-range (two rows in Table 18), e.g. the sub-range "low" (0-0.2) is divided into 0-0.1 and 0.11-0.2 to acknowledge whether a value lies in the higher or lower part of the sub-range and to distribute the major part of the 100% accordingly.

Table 18: Conversion table for values 0-1 for nodes with five states.

Sub-ranges		very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
very low (0-0.2)	0-0.1	90	10	0	0	0
	0.11-0.2	80	15	5	0	0
low (0.21-0.4)	0.21-0.3	15	80	5	0	0
	0.31-0.4	5	80	15	0	0
medium (0.41-0.6)	0.41-0.5	0	15	80	5	0
	0.51-0.6	0	5	80	15	0
high (0.61-0.8)	0.61-0.7	0	0	15	80	5
	0.71-0.8	0	0	5	80	15
very high (0.81-1)	0.81-0.9	0	0	5	15	80
	0.91-1	0	0	0	10	90

This conversion table was used to convert the weighted average values of the two nodes on "Plant-specific irrigation needs" for plant species in the urban and the peri-urban area. For example, the weighted average value for the irrigation need of *Ailanthus altissima (M.) Swing.* is 0.23 (see Table D - 5). This value lies in the sub-range low (0.21-0.40). As it lies in higher end of the sub-range (0.21-3), the probability distribution in the CPT is: 15% very low, 80% low, 5% medium (Table 19).

With the same procedure, a conversion table for values between 0-3 for nodes with three states was created (Table 20). This conversion table was used to convert the weighted average values of "Plant-specific shading", "Plant specific soil protection", "Plant-specific wind protection", and "Plant specific dust filter".

Table 19: Conditional probability values for three peri-urban plant species.

Plant species	Weighted average	Sub-range	Irrigation needs of plant species				
			very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
Ailanthus altissima (M.) Swing.	0.23	0.21-0.3	15	80	5	0	0
Elaeagnus augustifolia L.	0.13	0.11-0.2	80	15	5	0	0
Fraxinus sogdiana Bunge.	0.56	0.51-0.6	0	5	80	15	0

Table 20: Conversion table for values 0-3 for nodes with three states.

	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1.0	80	15	5
1.1-2.0	10	80	10
2.1-3	5	15	80

4.2.3.2 Building conditional probability tables from equations

Six child nodes (●) are parameterized with the help of simple equations that equally weight their incoming parent nodes (see Table B - 3 in Appendix B). All equations represent positive correlations. The higher the “Shade by urban vegetation” and the “Dust weather mitigation by vegetation”, the higher the level of “Ecosystem services” provided. The higher the “Plant-specific irrigation needs” and the “Vegetation cover in % of urban area”, the higher the “Irrigation needs in urban area”. The node “Dust weather mitigation by plants” is summarizing the impacts of its three parent nodes. For this summary node, the participants of WS 2 and 3 were asked which parent node was more influential than the others. Due to lack of consensus among the experts, the parent nodes were equally weighted to have an unbiased version.

For equations in Netica, each state of the parent nodes need assigned state values (“state numbers”). For “Plant-specific soil protection”, the state “low” has the state value 0, “medium” 1, and “high” 2. For this purpose, all states of the parent nodes need to be arranged in the same order. For the node “Dust weather mitigation by plants”, the following equation is entered in the respective window of its node dialog box:

plant_dust_mitigation (plant_dust_filter, plant_soil_protection, plant_wind_protection) = plant_dust_filter+plant_soil_protection+ plant_wind_protection)/6

Using the names of the nodes, the equation says that the sum of the state values of the parent nodes should be divided by 6 which is the highest number that can be reached. If all parent nodes were in state “low” (state value 0), the calculation would be (0+0+0)/6 = 0; if all parent nodes were in state “high” (state value 2) the calculation would be (2+2+2)/6 = 1. This way, the result lies between 0-1. Therefore, the states of the child node needed assigned discretization intervals between 0-1, such as “low” (0-0.33), “medium” (0.33-0.66), and “high” (0.66-1). In a last step, Netica needs to be told to derive the CPT from the equation with the command “Equation to table”.

To derive CPTs from equations in Netica, some nodes need to be discrete while others need to be continuous. The parent nodes, e.g. “Plant-specific soil protection”, need to be discrete as each state gets only one assigned state number. The child node for which the CPT is derived by an equation, e.g. “Dust weather mitigation by plants”, needs to be continuous as the result of the equation could be any number between 0 and 1. The assigned discretization intervals of the continuous node make sure that the result of the equation can be represented by three discrete states. In the final BN, three nodes needed to be child and parent nodes for equations at the same time. As the nodes could not be discrete and continuous at once, three additional nodes were created (see Figure 30).

plant_dust_mit	Dust weather mitigation by plan...
low	low
medium	medium
high	high

Figure 29: Deterministic conditional probability table for "Dust weather mitigation by plants".

Deterministic CPTs ensured that these three additional nodes had exactly the same probability distribution as their respective parent node (Figure 29). These nodes solely served as discrete parent nodes for the next equations and were hidden in the final BN to avoid confusion (see Figure 28). In Netica, nodes can easily be positioned above other nodes without leaving a trace – the BN could still be used to compare the impact of different root nodes on the leaf nodes.

The BN that was presented and used at WS 3 needed to consist of 16 nodes in order to be able to use Netica's "Limited mode". For this purpose, the CPTs that were created by the equations were copied into a version without these three additional nodes.

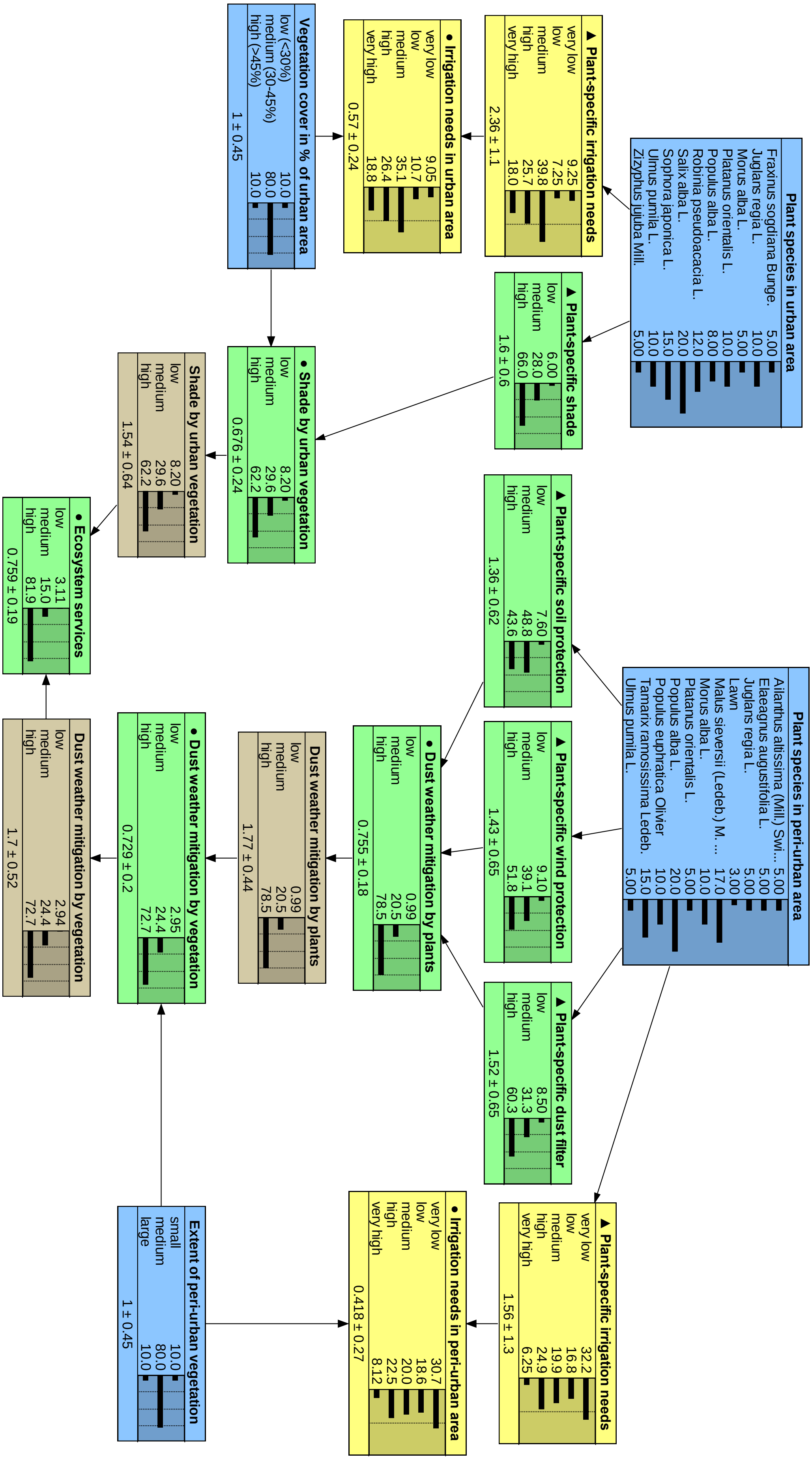


Figure 30: Final ESS BN with additional deterministic nodes disclosed.

4.3. Model application

The parameterized ESS BN can be used top-down to compare the impact of different states of the four root nodes on the leaf nodes “Ecosystem services” and “Irrigation needs” (urban and peri-urban). Whenever the probability distribution in one of the root nodes is changed, Netica recalculates the probability distributions of all child and leaf nodes. The ESS BN can be used to compare single plant species with each other or to compare combinations of plant species. In addition, the extent of peri-urban vegetation and the vegetation cover in the peri-urban area can be increased or decreased. An increase of vegetation basically leads to increased “Ecosystem services” but also to increased “Irrigation needs”. A decrease of vegetation has the opposite effect.

The plan was to ask the participants of the final workshop (1) to get acquainted with Netica by doing exercises with simple BN examples, (2) to compare single plant species with the ESS BN, and (3) to find combinations of urban and peri-urban plant species that provided a “high” level of “Ecosystem services” with “very low” or at least “low” irrigation needs. Setting the probability of a single plant species to 100% would mean that only this one plant species was planted in the whole urban or peri-urban area. Of course, such a monoculture was neither realistic nor desirable. The 100% should be distributed across more than one state which was difficult due to the high number states. To assist the WS participants in solving this third task, two Bayesian Decision Networks (BDNs) were developed in addition to the already existing ESS BN. This chapter introduces the two BDNs (Chapter 4.3.1) and presents how the final ESS BN and the results from the BDNs were applied during WS 3 in March 2014 (Chapter 4.3.2).

4.3.1. Add-on: Bayesian Decision Networks

BDNs are mainly used to assess which management option has the highest benefit at the lowest monetary costs. Here, the idea was to conduct a cost-benefit analysis for plant species.

4.3.1.1 Bayesian Decision Network "Dust"

The Dust BDN aims at identifying which peri-urban plant species is most suitable for dust weather mitigation (= utility) while needing the least irrigation (= costs). Therefore, the root node "Plant species in peri-urban area" is used as decision node and the plant species can be seen as management options. A directed link points from the decision node to the utility node for costs (Figure 31). For each plant species a value between -1 and 0 was entered in the utility table. As expert group A, B, and C assigned the minimum (0 = lowest need) and maximum (1 = highest need) to the same peri-urban plant species, the weighted average values could easily be turned into negative values and used as input for the utility node "Irrigation needs (= costs)". Only for five plant species the irrigation needs were elicited twice and therefore averaged (see Table D - 7 and Table D - 8).

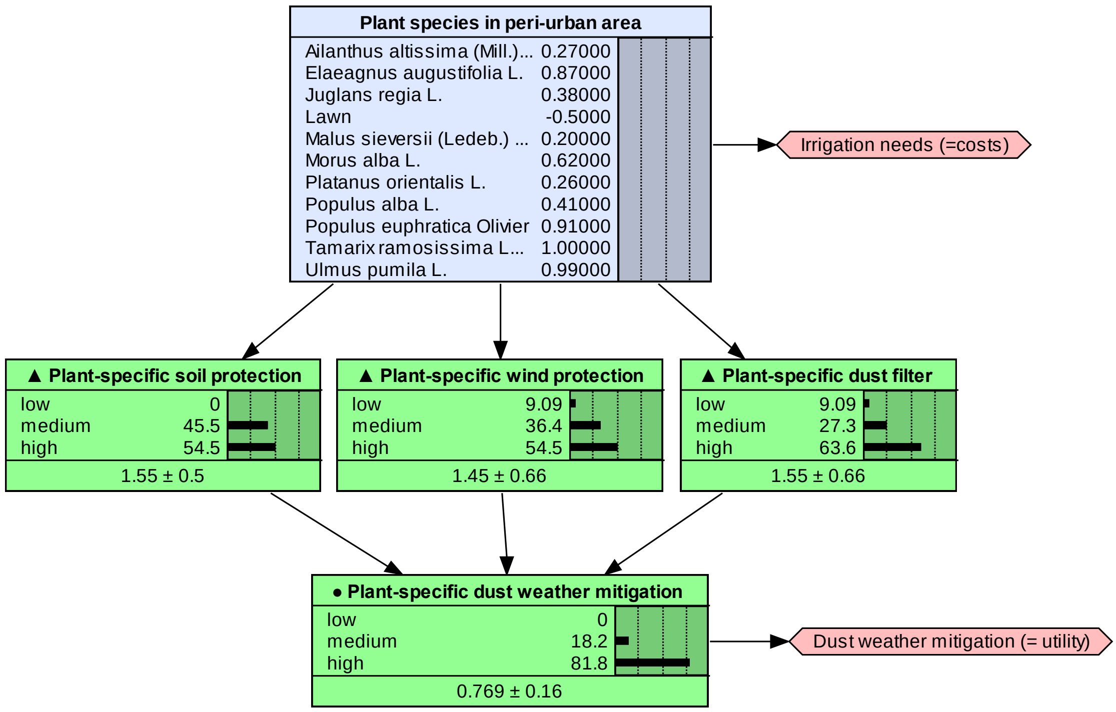


Figure 31: Bayesian Decision Network "Dust".

Another link points from the leaf node “Plant-specific dust weather mitigation” to the utility node for benefits. For each state of the leaf node a numerical value between 0 and +1 was entered in the table of “Dust weather mitigation (= utility)”: the minimum (0) was assigned to “low”, the maximum (+1) to “high”, and the mean value 0.5 to “medium”.

For the expert-based nodes (▲), the weighted average of the experts’ estimates was used. However, the conversion into conditional probability values was changed to calibrate the BDN in a way that the most effective plant species reached 100% “high” plant-specific dust weather mitigation and therefore the highest utility. The new conversion table (Table 21) leads to deterministic CPTs which ensure that the highest utility (+1) is put on a par with the highest costs (-1). The leaf node (●) uses the same equation as the ESS BN which equally weights its three parent nodes.

Table 21: Bayesian Decision Network conversion table for values between 0-3 for nodes with three states.

	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1.0	100	0	0
1.1-2.0	0	100	0
2.1-3	0	0	100

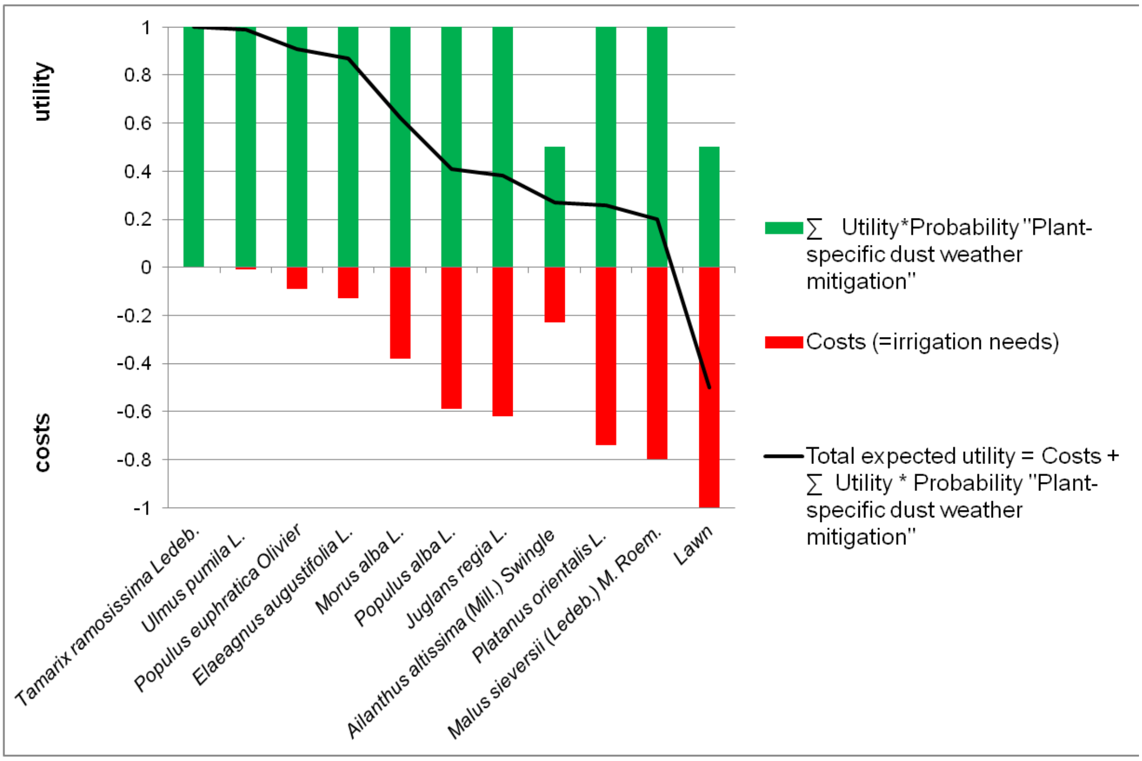


Figure 32: Results of the Bayesian Decision Network “Dust”.
The green bars represent the utility (0 to 1), the red bars the costs (0 to -1), and the graph shows the total expected utility for 11 peri-urban plant species.

The values in the decision node show the total expected utility for each state. As Netica does not change the order of the states according to their net benefits, the results were presented to the WS participants in three forms: (1) Print-outs of both BDNs, (2) bar charts (Figure 32), and (3) simple rankings.

4.3.1.2 Bayesian Decision Network "Shade"

The Shade BDN compares ten urban plant species in their ability to provide shade (= utility) and their irrigation needs (= costs) (Figure 33). The Heat BDN was developed in a similar way as the Dust BDN – with the same conversion table and the same values in the table of "Plant-specific shade (= utility)". Only the experts' estimates on urban irrigation needs could not be directly entered into the utility table of "Irrigation needs (= costs)". When the experts' estimates on urban irrigation needs were elicited at WS 2, the table still included "lawn" due to the cooling effect of evapotranspiration. After the variable "Evapotranspiration" had not been transferred to the ESS BN, there was no urban plant species with maximum irrigation needs (1) left. Therefore, the values for the utility node "Irrigation needs (= costs)" needed to be standardized (see Table D - 9 and Table D - 10 in Appendix D).

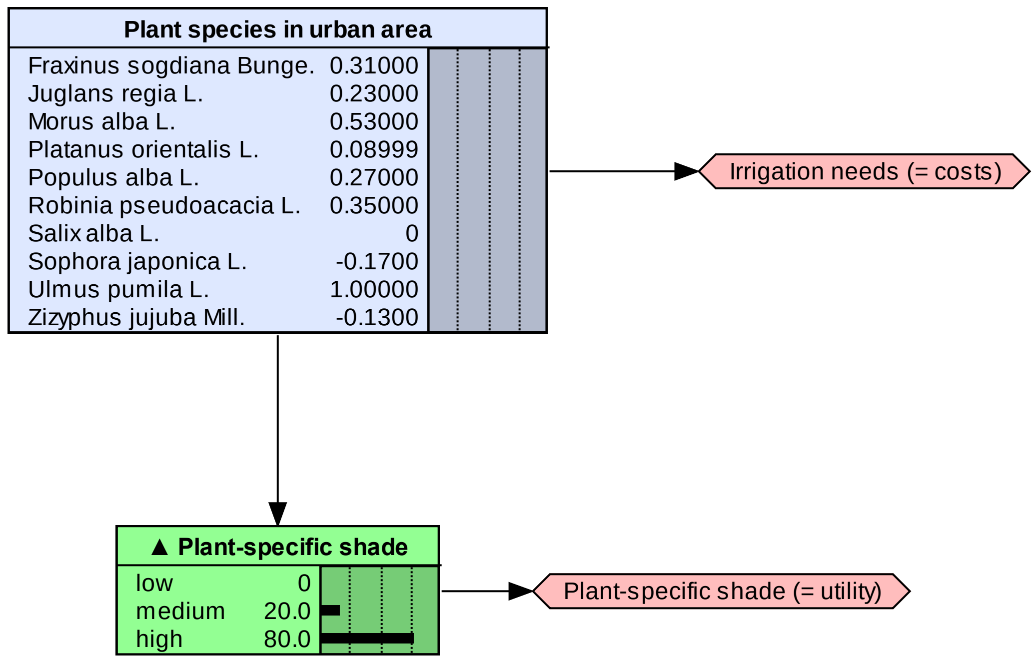


Figure 33: Bayesian Decision Network "Shade".

4.3.2. Bayesian Network application during expert workshop 3

WS 3 took place in Urumqi on 11th March 2014 and was titled “Sino-German Workshop on Ecosystem Services of Urban and Peri-urban Forests in Oasis Cities of Xinjiang: The role of forests in relieving dust & urban heat” (Table C - 3). The aim of WS 3 was to first make the participants acquainted with the BN software Netica in order to enable them to use and evaluate the final ESS BN.

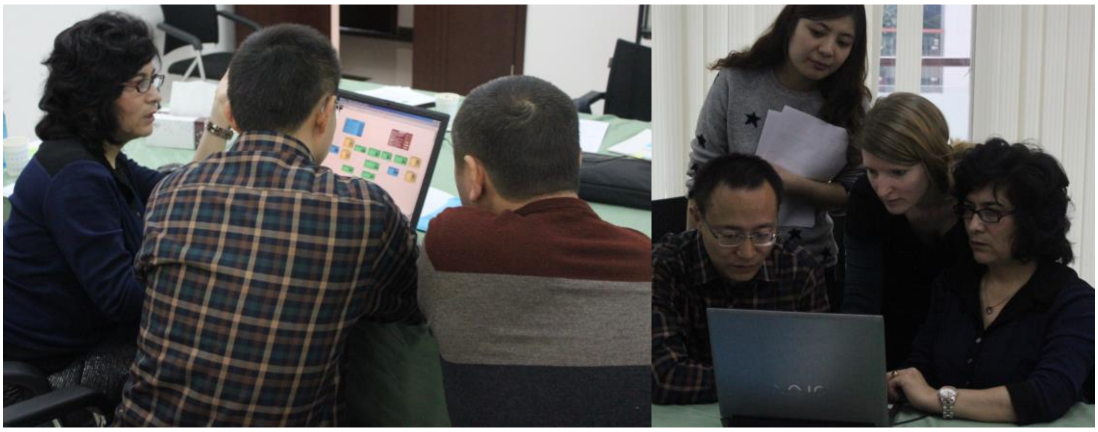


Figure 34: Bayesian Network application during WS 3, Urumqi, 11th March 2014.

As only four of the seven participants attended either WS 1 or WS 2, the workshop started with an introduction to the SuMaRiO project and a thorough introduction to BN modeling during which the experts had to do little exercises with small example BNs in Netica’s limited mode. After they had become familiar with Netica’s most important functionalities, the ESS BN was presented. In groups of 2-3 experts, they were asked to compare single plant species and to find good combinations of plant species that provided “high” levels of ecosystem services while having “low” or “very low” irrigation needs (Figure 34). After 10-15 minutes, the BDN method and the results of the two BDNs were introduced to the participants. After the participants received print-outs of the BDNs and the resultant rankings, they again worked with Netica for another 15-20 minutes. The groups took notes and discussed the outcomes among as well as between the small groups.

In the retrospect, the documentation of results could have been improved. If each group would have written on cards (1) which combination of plant species they have chosen (by manually changing the tables of the root nodes) and (2) how the probability distributions in the leaf nodes changed, overlaps could have been prevented. Without such documentation, groups chose and tested very similar combinations. A collection of results on a pin board could also have served as basis for a final group discussion. However, such an improved documentation and discussion of results would have required more time.

4.4. Model evaluation

The expert-based BN was evaluated in different ways. This chapter first presents how model sensitivity was analyzed with conventional sensitivity analysis tools and newly developed methods which specifically address the conversion into conditional probability values (Chapter 4.4.1). Then, it summarizes how participants of WS 3 evaluated the usefulness of the model output for local vegetation management and the BN method for environmental management in general (Chapter 4.4.2).

4.4.1. Sensitivity analyses

The model sensitivity was tested in three different ways. First, the sensitivity to findings was analyzed. Then, the sensitivity of the model to changes in the conversion method was tested. In absence of validation data, the sensitivity of the output variables to input from expert groups A, B, and C was finally compared.

4.4.1.1 Sensitivity to findings

To analyze the sensitivity of a query node to findings in other nodes, Netica uses variance reduction calculations for continuous variables and entropy reduction calculations for discrete variables (Chen and Pollino, 2012). With this, it is possible to generate a ranking that shows how much the query node is influenced by the other nodes. The values for variance reduction and entropy reduction can range between 0 which means the variable has no influence on the query node to the value of full variance or full entropy of the query node (see Chapter 2.4.2).

Here, two child nodes were selected to check whether the ESS BN as well as the inbuilt equations functioned well. Three rankings were created for the continuous variables "Ecosystem services", and "Dust weather mitigation by plants". The node "Ecosystem services" is more sensitive to findings at "Shade by urban vegetation" than by "Dust weather mitigation by vegetation" (Figure 35). This seems surprising at first as the CPT of "Ecosystem services" was generated with the help of an equation that equally weighted the parent nodes. This shows the difference between the strength of causal relationships between variables (represented by the CPTs) and sensitivity between variables.

The sensitivity analysis reveals how sensitive the query node reacts to changes in other nodes given the findings entered at the time. Here, the probability distribution of "Shade by urban vegetation" is rather flat (see Figure 30). This is why alterations in its probability distribution, e.g. to 100% low or 100% high, would lead to more distinct changes in the probability distribution of "Ecosystem services" than changes in the other direct parent node.

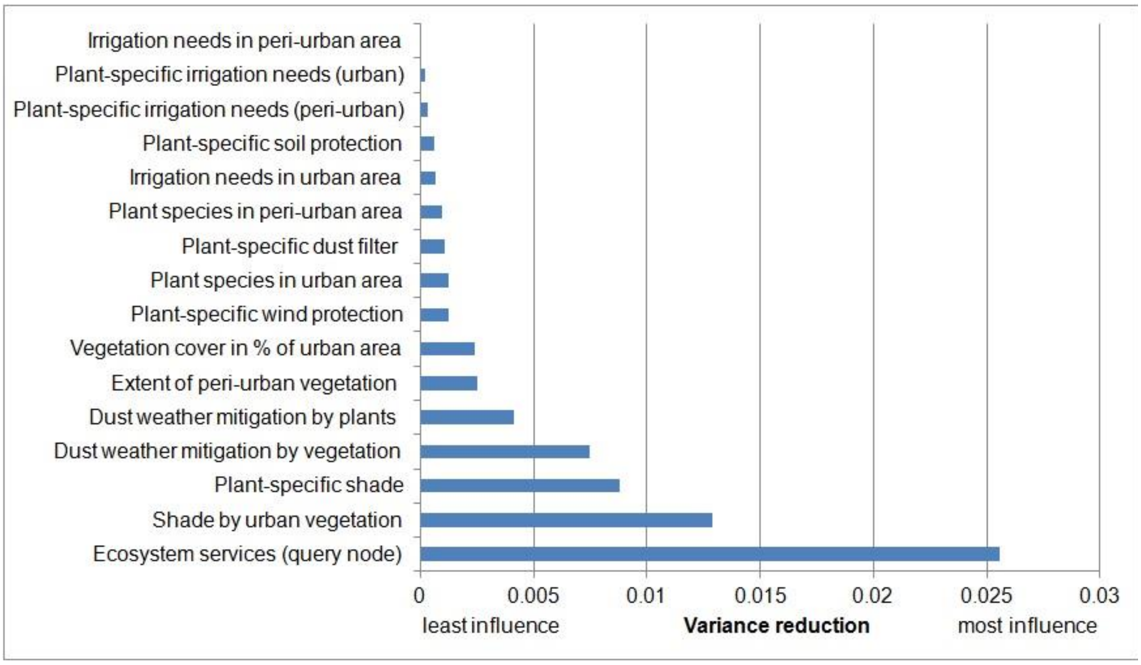


Figure 35: Sensitivity analysis results for "Ecosystem services". Given the same probability tables (PTs) as in Figure 30.

Sensitivity to findings can also be used to check if parts of the network which should be independent of each other are successfully *d*-separated by the network structure. The fact that "Dust weather mitigation by plants" solely reacts to changes in nodes related to peri-urban vegetation (Figure 36, at the top) highlights that the two parts of the ESS BN – dust weather mitigation by peri-urban vegetation and the provision of shade by urban vegetation – do not influence each other. In addition, sensitivity to findings was used to check whether the inbuilt equations work as they are supposed to. For example, when *Ailanthus altissima (Mill.) Swingle* is selected as state of the node "Peri-urban plants", the three child nodes have exactly the same probability distributions (according to the weighted average of the experts' estimates) and therefore exactly the same influence on their child node (Figure 36, at the bottom).

These analyses confirmed that the BN performs exactly the way it should. With a high number of equations in place, the selection of states in the four root nodes highly influences the resultant rankings. The sensitivity of each query node would have looked differently if the PTs were changed before Netica performs the variance reduction calculations.

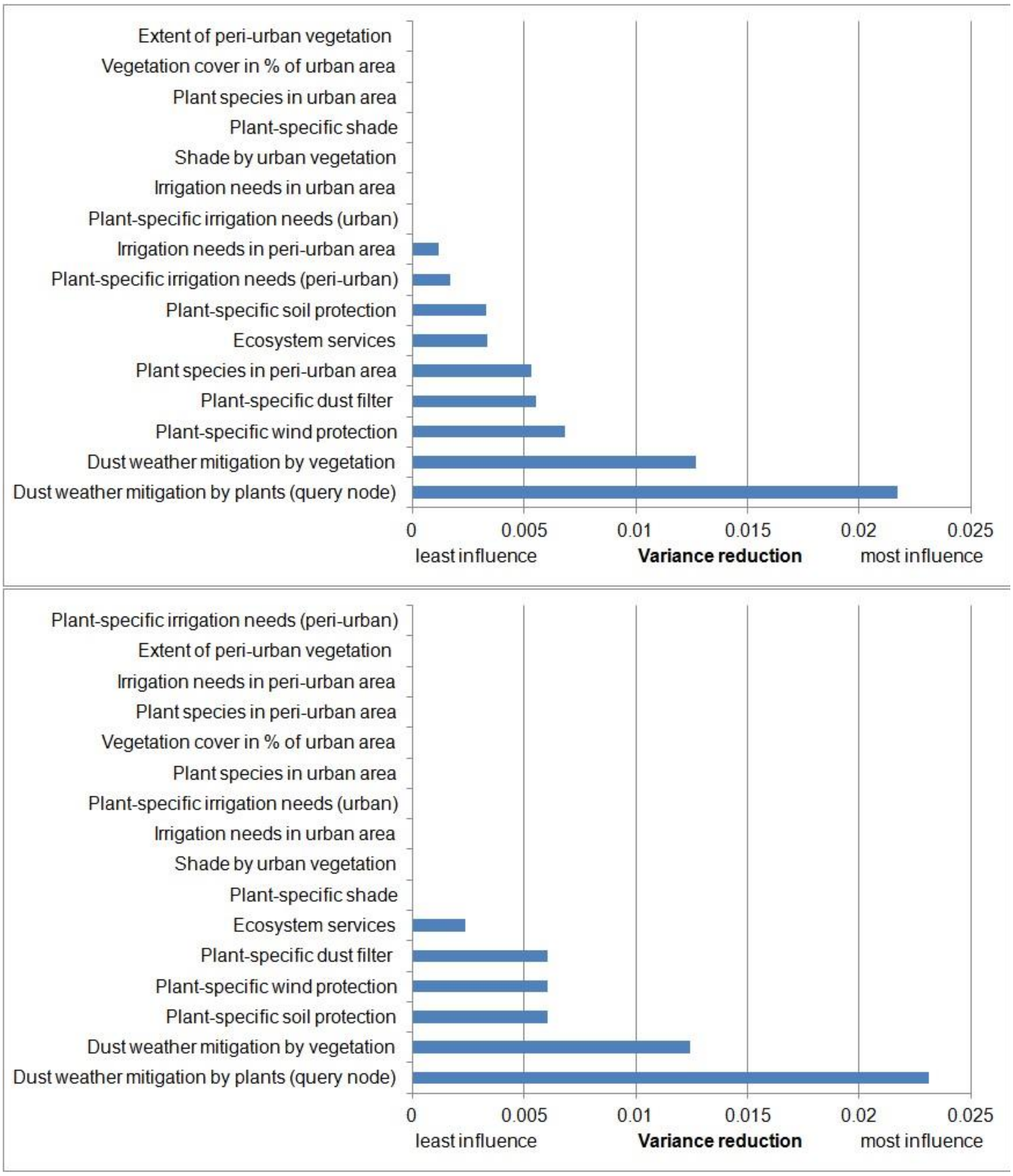


Figure 36: Sensitivity analysis results for "Dust weather mitigation by plants". At the top, given the same probability tables (PTs) as in Figure 30; at the bottom, given the root node "Plant species in peri-urban area" is in state *Ailanthus altissima (Mill.) Swingle* (100%) and other probability tables (PTs) as in Figure 30.

4.4.1.2 Sensitivity to conversion tables

The final ESS BN consists of 19 nodes with 4 unconditional probability tables (PTs) and 15 conditional probability tables (CPTs). Nine of these CPTs are deterministic due to the use of six equations (●) and the addition of three deterministic nodes to realize the equations (see Chapter 4.2.3.2). The probability distributions of these nine nodes in the lower part of the BN are determined by their CPTs which result from in-built equations. The six remaining CPTs (▲) are probabilistic and result from the conditional probability values conversion method introduced in Chapter 4.2.3.1. As this high number of deterministic CPTs impedes analyzing the sensitivity to parameters, the sensitivity of the leaf nodes to changes in the conversion is analyzed instead.

Converting the weighted average values of experts' estimates into conditional probability values gives a lot of responsibility or power back to the modeler. Whether values are converted into distinct (or "sharp") probability distributions such as 90:10 or 80:20 or very flat distributions such as 60:40 or 50:50 can make all the difference. This is why, four different conversion tables were created for values between 0-1 and values between 0-3 (Table 22; see also Table E - 1 and Table E - 2 in Appendix E). The conditioning or auxiliary node "Confidence in experts' estimates" was added to give the model user the possibility to decide which conversion table should be used (Figure 37). The model user can choose between the states "very low", "rather low", "rather high", and "very high" according to his or her confidence in the experts' estimates.

Table 22: Conversion tables for values between 0-3 for nodes with 3 states for four levels of confidence in experts' estimates.

very unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	50	30	20
1.1-2	25	50	25
2.1-3	20	30	50
rather unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	60	25	15
1.1-2	20	60	20
2.1-3	15	25	60
rather confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	70	20	10
1.1-2	15	70	15
2.1-3	10	20	70
very confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	80	15	5
1.1-2	10	80	10
2.1-3	5	15	80

The less confident the model user is in the experts' estimates, the wider is the probability distributed over the output states. For example, if the "Confidence in experts' estimates" is "very low", the BN uses the respective "very unconfident" conversion tables for all expert-based CPTs. The "very unconfident" conversion table for values between 0.41-0.5 distributes only 50% in the "medium" state, whereas the "very confident" conversion table distributes 80% in the "medium" state (see Figure 38).

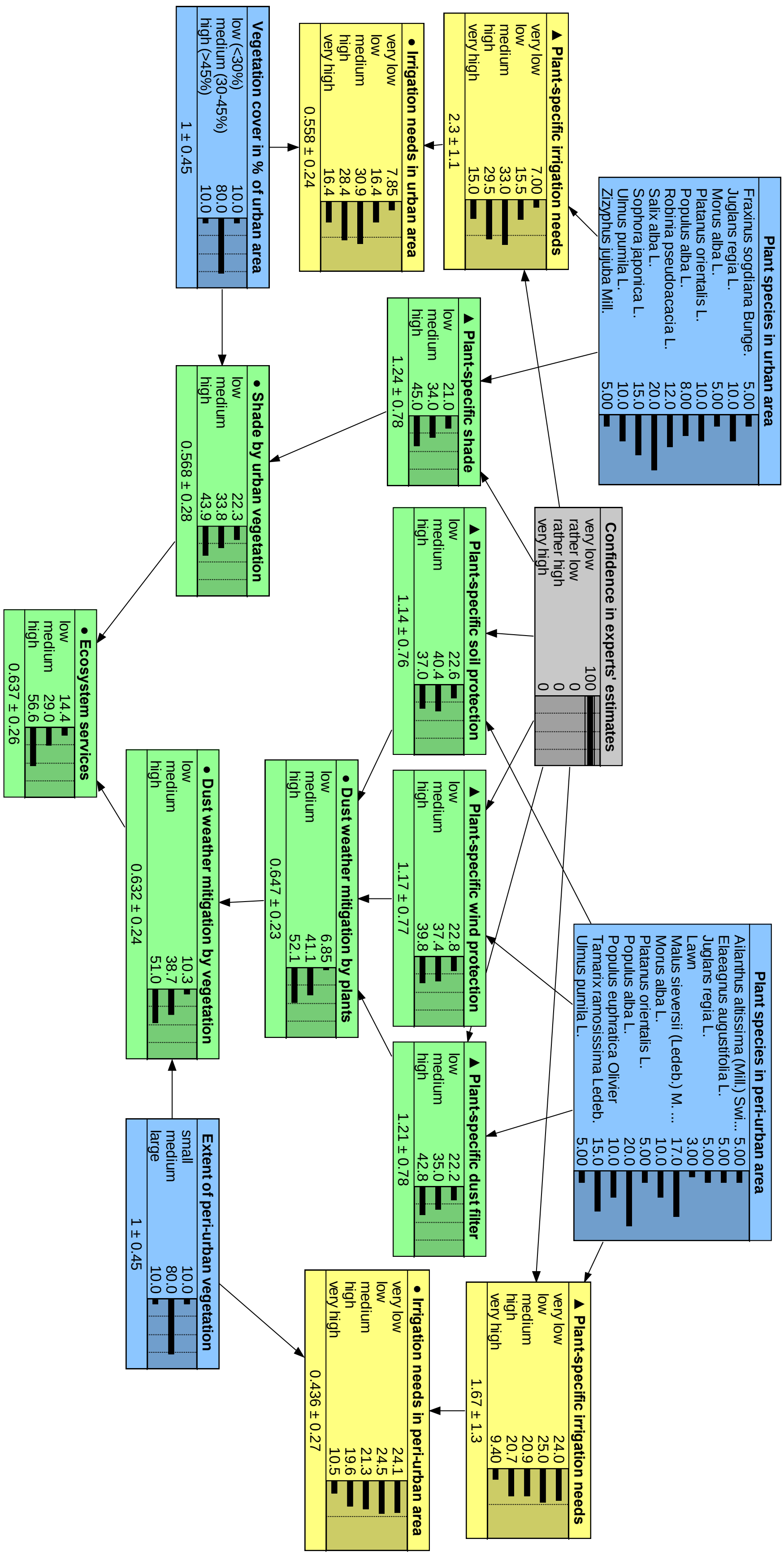


Figure 37: Final ESS BN with auxiliary node "Confidence in experts' estimates". Given the same probability tables (PTs) as in Figure 30.

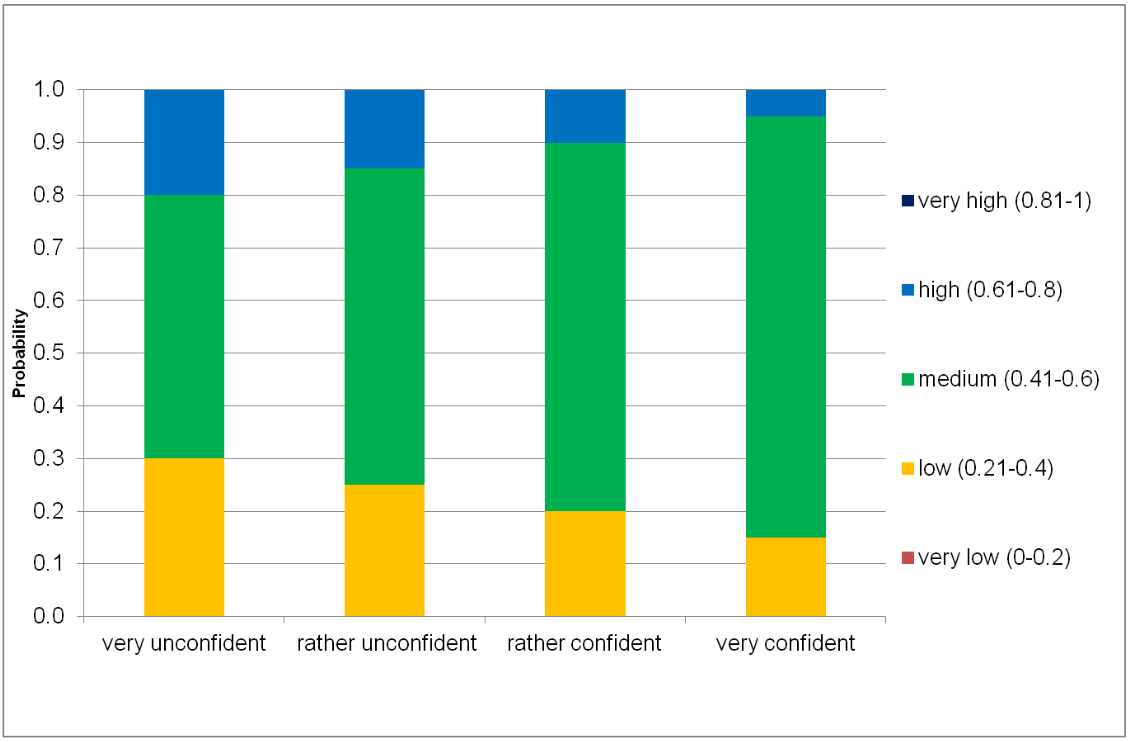
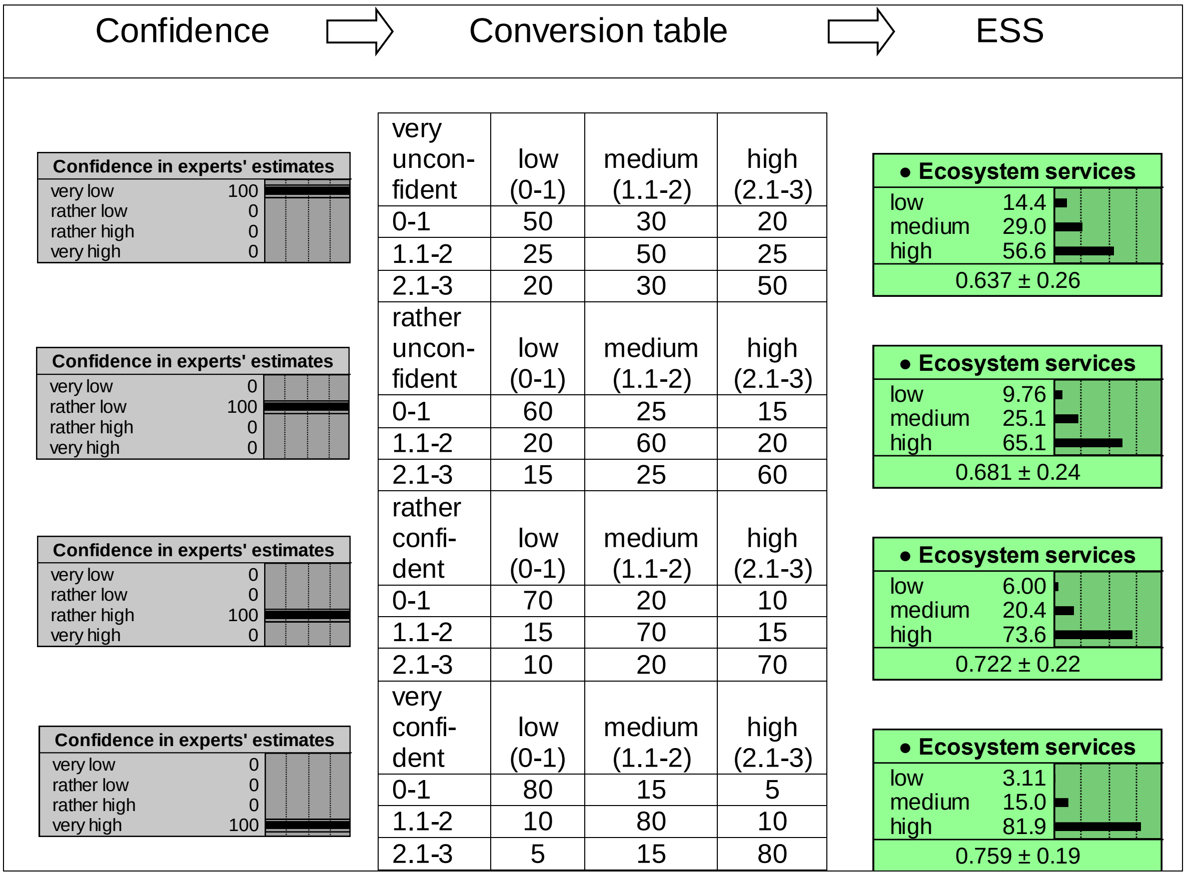


Figure 38: Probability distributions for values between 0.41-0.5 based on four conversion tables for values between 0-1 for nodes with 5 states.
The columns represent the four conversion tables (“very unconfident”, “rather unconfident”, “rather confident”, “very confident”) (see Table E - 1).

The output variable “Ecosystem services” is very sensitive to changes in this confidence-based conversion method. With increasing confidence in the experts’ estimates, the probability of “high” “Ecosystem services” provided by certain urban and peri-urban plant species increases from 59.6% to 87.3% (Figure 39). In contrast, the probability of “very low” “Plant-specific irrigation needs” only increases from 24% to 32.2% (see Figure 40). This is related to the fact that the probability distribution of “Plant-specific irrigation needs” for the selected peri-urban plants was widely distributed – no matter which conversion table was used.

The extra node “Confidence in experts’ estimates” with its six links to the expert-based nodes (▲) leads to an increase of probability values in the ESS BN. Whereas the final ESS BN has 600 conditional and unconditional probability values; the ESS BN with the extra node has 1306 probability values. For example, after the inclusion of the extra node the CPTs of “Plant-specific soil protection”, “Plant-specific wind protection”, and “Plant-specific dust filter” has 3x44 conditional probability values each.

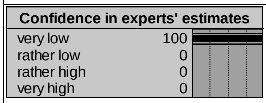


very unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	50	30	20
1.1-2	25	50	25
2.1-3	20	30	50
rather unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	60	25	15
1.1-2	20	60	20
2.1-3	15	25	60
rather confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	70	20	10
1.1-2	15	70	15
2.1-3	10	20	70
very confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	80	15	5
1.1-2	10	80	10
2.1-3	5	15	80

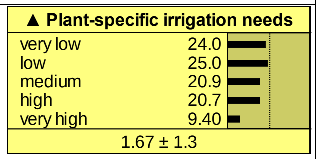
Figure 39: Sensitivity of "Ecosystem Services" to different conversion tables. Given the same probability tables (PTs) as in Figure 30.

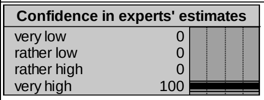
Due to time constraints, the ESS BN with the additional node "Confidence in experts' estimates" could not be presented during the final expert workshop. For the BN that was presented during WS 3 (see Figure 28), the "very confident" conversion tables were used (see Table 22).

Confidence	⇨	Conversion table	⇨	Plant specific peri-urban irrigation needs



	very unconfi-dent	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
	0-0.1	60	40	0	0	0
	0.11-0.2	50	30	20	0	0
	0.21-0.3	30	50	20	0	0
	0.31-0.4	20	50	30	0	0
	0.41-0.5	0	30	50	20	0
	0.51-0.6	0	20	50	30	0
	0.61-0.7	0	0	30	50	20
	0.71-0.8	0	0	20	50	30
	0.81-0.9	0	0	20	30	50
	0.91-1	0	0	0	40	60





	very confi-dent	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
	0-0.1	90	10	0	0	0
	0.11-0.2	80	15	5	0	0
	0.21-0.3	15	80	5	0	0
	0.31-0.4	5	80	15	0	0
	0.41-0.5	0	15	80	5	0
	0.51-0.6	0	5	80	15	0
	0.61-0.7	0	0	15	80	5
	0.71-0.8	0	0	5	80	15
	0.81-0.9	0	0	5	15	80
	0.91-1	0	0	0	10	90

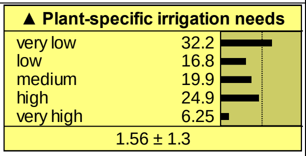


Figure 40: Sensitivity of "Plant-specific irrigation needs" to different conversion tables. Given the same probability tables (PTs) as in Figure 30.

4.4.1.3 Sensitivity to expert groups

Another recommendation given during the research stay in Australia was to compare the estimates of the different expert groups. As the estimates of expert groups A, B, and C were the only input data, the results of the ESS BN could be easily contested. However, showing that different expert groups come to very similar outcomes could improve the reliability or explanatory power of the ESS BN. Therefore the conditioning or auxiliary node "Expert groups" was added to the network structure (see Figure 42). Exactly as the node "Confidence in experts' estimates" (see Chapter 4.4.1.2), the node has four states and is linked to the six expert-based nodes (▲). This extra node also increases the number of probability values from 600 to 1306.

Estimates and confidence of expert groups

Expert group A mainly used the medium categories (+ and ++), expert group B straightforwardly used the highest category (+++), and expert C tended to use the medium category (++) to rate the plant-species (Figure 41). While evaluating the 11 peri-urban and 10 urban plant species in their ability to stabilize the soil, to protect from wind, to filter dust and to provide shade, expert group B assigned the highest ratings. In average, they assessed the ability of all plants to perform these plant-specific services between "high" (++ or 2) and "very high" (+++ or 3) (see Figure 43).

Despite the different use of the categories between the expert groups, the highest and lowest values were assigned to the same plant species. For example, all expert groups identified *Tamarix ramosissima Ledeb.* as peri-urban plant with the lowest and lawn as peri-urban plant with the highest irrigation need. In the same way, the node "Dust weather mitigation by plants" revealed that the peri-urban plants *Populus euphratica* OLIVIER and *Elaeagnus augustifolia L.* were most suitable to mitigate dust weather according to all experts' assessment. The variations in confidence lead to different probability distributions in the node "Dust weather mitigation by plants" but the estimates of each group identified the same two plant species to be most effective[13].

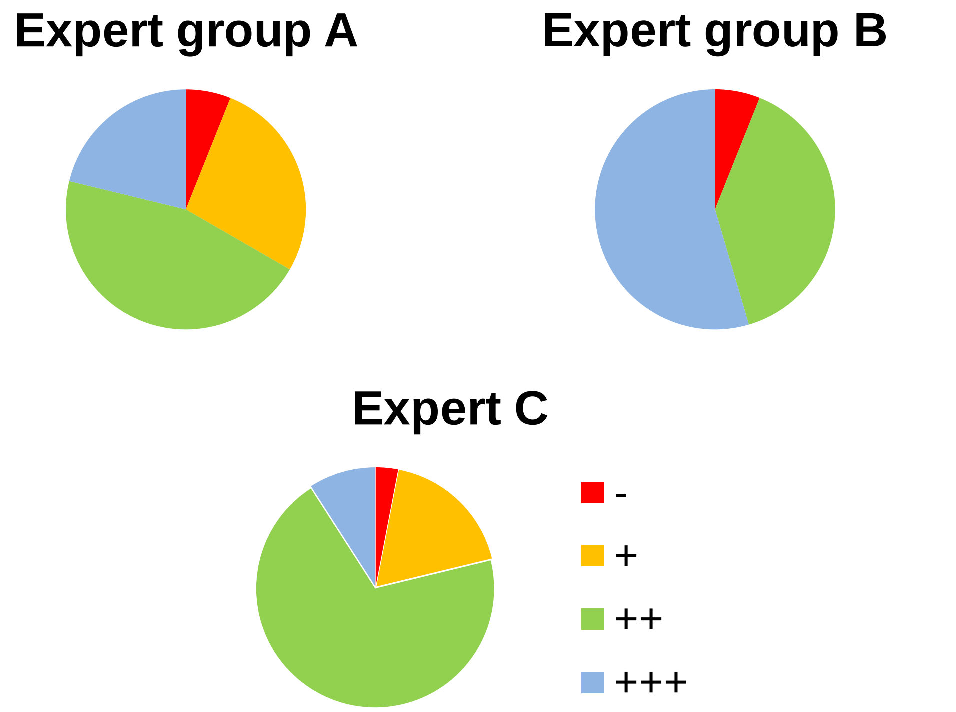


Figure 41: Used categories (-, +, ++, +++) to express the plant-specific services for all plant species by expert group.

[13] Expert groups A and B identified more than two plant species leading to the highest "Dust weather mitigation by plants".

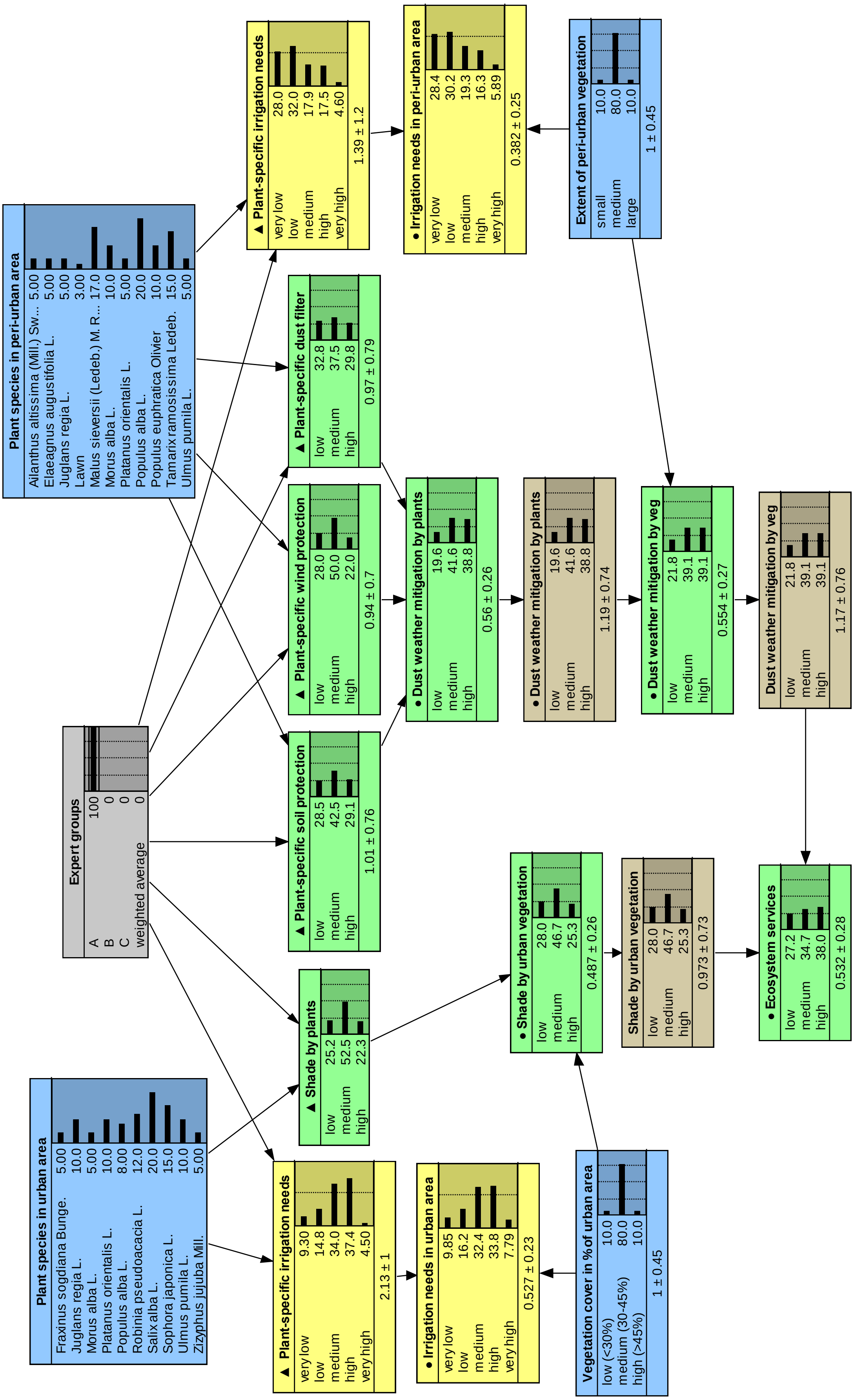


Figure 42: Final ESS BN with auxiliary node "Expert groups". Given the same probability tables (PTs) as in Figure 30.

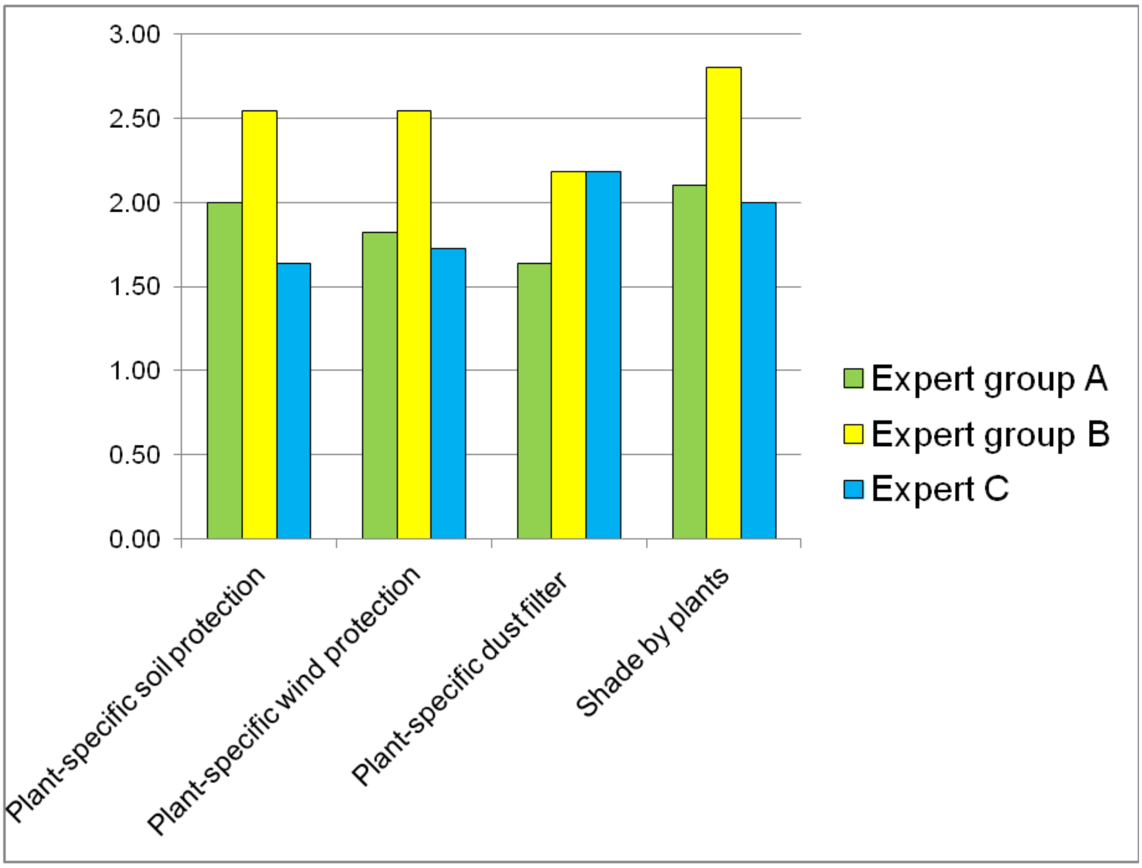


Figure 43: Average values for all plant species by expert group.

The expert groups also agreed on “Plant-specific soil protection” of peri-urban plant species. The elicited ratings on a scale of – to +++ (0-3) do not differ by more than one unit for each plant species. This clearly shows which plant species are perceived to be most and least suitable to stabilize the soil (Figure 44). All expert groups stated that *Populus alba L.* has a “high” (++) capacity to stabilize the soil. Only in this case, the weighted average is the same as the average. For all other estimates, the weighted average is slightly above the average. This deviation is mainly influenced by expert group B which used the highest categories and had the highest confidence in all of their estimates. Expert groups A was “rather confident” and expert group B was “very confident” in all of their estimates; only expert C differentiated the confidence by reflecting on experience in each field (see Table 17). These confidence levels determined which conversion tables were used to generate the CPTs.

All estimates of expert group A were converted with the “rather confident” conversion table, all estimates of expert group B were converted with the “very confident” conversion tables, and the estimates of expert C were either converted with “rather confident” or “very confident” conversion tables consequently. To make different levels of confidence transparent, the node “Confidence of expert group” was linked to the node “Expert groups” in the ESS BN (Figure 45).

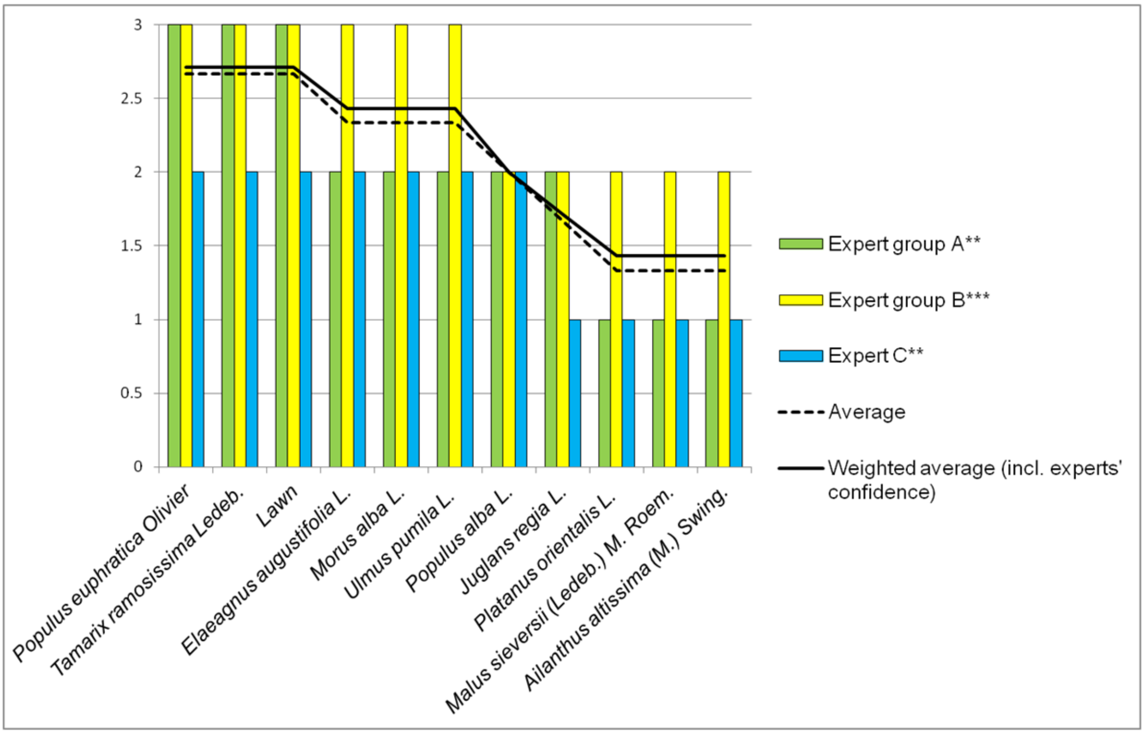


Figure 44: Values for "Plant-specific soil protection" of 11 peri-urban plants by expert group.

** and *** indicate confidence of expert groups (see Table 17).

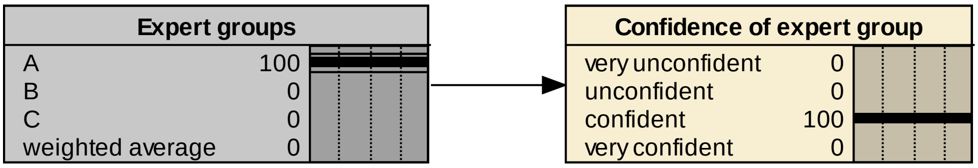


Figure 45: Extra node "Confidence of expert groups" added to the final ESS BN with the auxiliary node "Expert groups" (see Figure 42).

Comparison of BN outputs by expert groups

Due to the differences in confidence and the related use of different conversion tables, the probability distributions in the output variable “Ecosystem Services” differs between the expert groups. With the same selection of states in the root nodes, the estimates of expert group A and expert C lead to wide probability distributions over all states, whereas the estimates of expert group B lead to a high probability in one state (“high”, 83.4%) (Figure 46).

The estimates of expert group A result in the highest “Ecosystem services” when *Morus alba L.* is selected as urban and *Populus euphratica* O*LIVIER* as peri-urban plant species (82.8%). According to expert group B, *Fraxinus sogdiana Bunge.* as well as seven other urban plant species and *Populus euphratica* O*LIVIER* as peri-urban plant species lead to the highest “Ecosystem services” (90.7%). The estimates of Expert C leads to the highest score if *Platanus orientalis L.* or *Populus alba L.* are selected as urban and *Populus alba L.* as peri-urban plant species (83.3%).

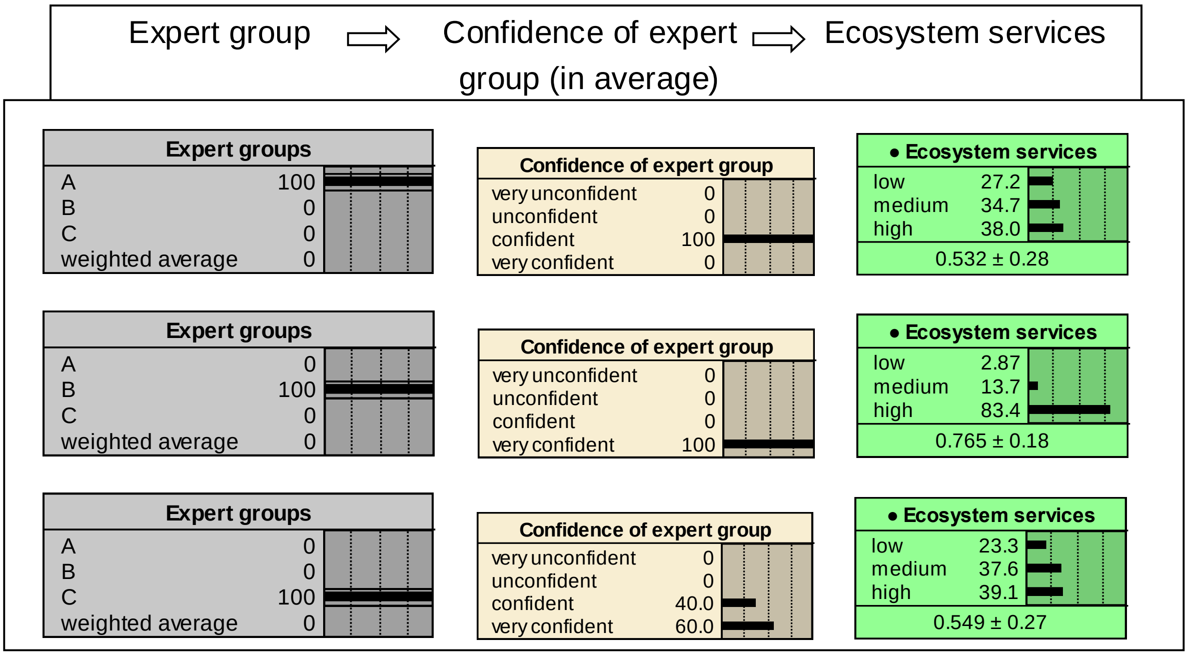


Figure 46: Probability distribution of “Ecosystem Services” and average confidence by expert groups.

4.4.2. Evaluation by experts

During WS 3, the participants were asked to evaluate the usefulness of BN and BDN results and the applicability of BNs in general (see Figure C - 4 in Appendix C). With regard to the BDNs, five out of seven participants stated that the ranking of plant species (total expected utility) was “very useful” for local urban landscape planning and management. Most participants found it “much easier” to use the ESS BNs after they had been provided with the results from the BDNs (Figure 47). Here, a common mistake in questionnaire design was made. The questionnaire should have asked how easy it was for them to use the BN – both with and without the BDN results provided.

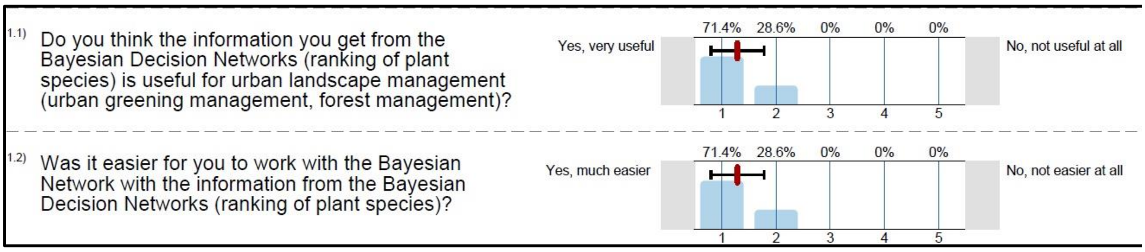


Figure 47: Results of the Bayesian Decision Network evaluation (n = 7).

With regard to the ESS BN, again five out of seven thought that the BN output was “very useful” for local urban landscape planning and management. Four participants stated that their system understanding of the problem fields improved “very much” by applying BNs during the workshop (Figure 48).

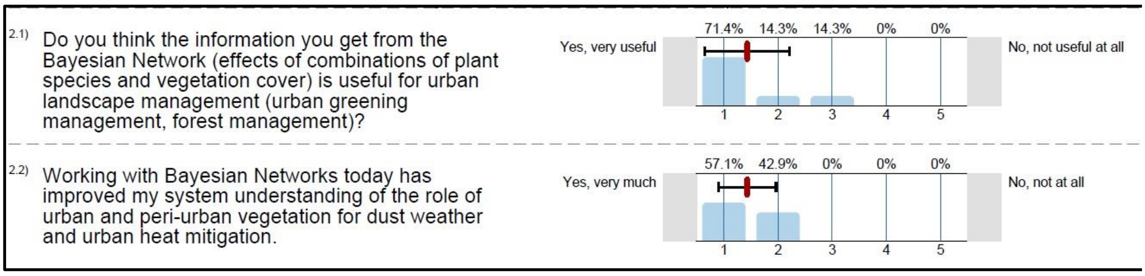


Figure 48: Results of the ESS BN evaluation (n = 7).

Five out of seven participants agreed that the BN method had a “very high” potential to be used more often for environmental management in the future (Figure 49). Most of the participants identified “improvement of systems understanding”, their potential for the “visualization of complex problems” and the “possibility to integrate experts’ knowledge” as benefits of BN modeling. Two participants viewed “difficulties in understanding conditional probabilities” and “difficulties with model output (probability distribution)” as challenges of BN modeling. One participant added another challenge in the empty field: “The reliability of the input data”.

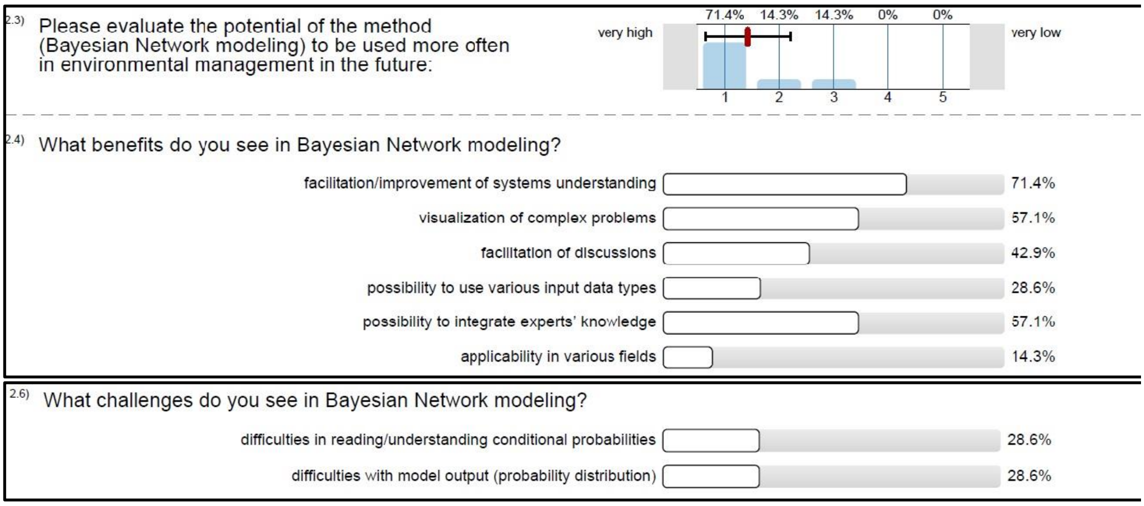


Figure 49: Results of the evaluation of the BN method in general (n = 7).

4.5. Bayesian Networks training course in Urumqi

To introduce the BN method to interested local students and researchers, a 4-hour training course on BN modeling was organized in Urumqi on 11th March 2013. As the course took place on the same day and in the same venue as WS 3, three WS participants spontaneously decided to attend the BN training as well.

The BN training course was very successful as it attracted 19 participants from four different universities and research institutes in Urumqi (Figure 50). Among the participants were three post-doctoral researchers, 5 Ph.D. students and 11 Master students. The idea to strengthen local research capacities with a BN training course was highly appreciated by our local project partner.

Figure 50: Bayesian Network training course in Urumqi, 11th March 2013.

4.6. Discussion

From a methodological perspective, the case study in Xinjiang was used to analyze how parameters of expert-based BN models can be improved (RQ 1). To improve the efficiency of BN modeling processes for expert-based models (RQ 1.1), a new method for the model parameterization with expert knowledge was developed (see Chapter 4.2.3.1). To increase the reliability of expert-based BNs (RQ 1.2), new methods for the evaluation of expert-based parameters were applied (see Chapter 4.4.1.2 and Chapter 4.4.1.3). This chapter discusses different elicitation formats (Chapter 4.6.1), questions the procedure of combining expert beliefs (Chapter 4.6.2), and reflects on the combined application of Bayesian Networks (BNs) and Bayesian Decision Networks (BDNs) (Chapter 4.6.3).

4.6.1. Ease of expert elicitation and conversion of expert knowledge

Conditional probability values can be elicited directly or derived from other elicitation formats. The direct elicitation of conditional probability values is demanding and very time-consuming. One strategy to ease the elicitation is to reduce the number of values that need to be directly elicited with the structured elicitation and interpolation method devised by Cain (2001). Another strategy is to elicit expert knowledge in other formats, e.g. to derive conditional probability values from linguistic expressions in reports or interviews (Moglia et al., 2012), to ask experts for frequencies (Borsuk et al., 2001), to ask experts for unconditional probability tables and weights for parent nodes (Baran et al., 2006; Baynes et al., 2011) instead of eliciting probabilities or percentage values. Independent from the elicitation format, a high ratio of assistants to experts can make the elicitation much easier for experts (Baynes et al., 2011; Catenacci and Giupponi, 2013).

It is rarely evaluated to which degree experts feel comfortable with getting involved in modeling processes. Drew and Collazo (2012) revealed that experts were most comfortable when they solely had to identify variables, already less comfortable when they had to rank these variables, and least comfortable when they were asked to provide probability values. In the case study Northwest China, the experts who attended WS 2 were asked which of the three elicitation formats used (0-1,– to +++, and conditional probability values) they preferred. Half of the experts favored to provide estimates in numerical values and the other half preferred to use the scale from – to +++. As expected, no one favored filling in conditional probability tables. The low number of experts involved in both case studies, e.g. four experts in the work of Drew and Collazo (2012), makes it difficult to generalize these results.

With extremely short workshop durations and only few workshop assistants during WS 2, it was necessary to establish a novel elicitation format that was easily understandable and foremost time-efficient. The idea to elicit ratings on a scale of – to +++ and numerical values (0-1) suited this purpose (see Chapter 4.2.3.1). The categories are similar to elicitation formats used in related modeling approaches. For example, Varis et al. (2012) used assigned numerical values (-1 to +1) to describe the strengths between variables within a matrix representation of the model structure and Martin et al. (2005) elicited positive (+1), zero (0), and negative scores (-1) as input for their statistical model.

The review of 50 expert-based BN applications revealed that only two case studies elicited the preferences and estimates from experts and stakeholders using numerical values between -1 to 1 (Pellikka et al., 2005) and -2 to 2 (Newton et al., 2007). However, in these applications the numerical values represented the states of the child node. By selecting one of the numerical values, the respective child node gets assigned 100%. In contrast, the conversion method introduced in this thesis allows the translation of each numerical value in a probability distribution – with the possibility to convert single values into probability distributions across several states. This has the advantage that few elicited values can be used to generate a large number of conditional probability values. In a first step, probability ranges ("sub-ranges") were defined for the expert-based parameters. For this, the numerical values (0-1) were more suitable than the ratings (–, +, ++, +++). As the experts could express their belief in any value between 0-1, the nodes for "Irrigation needs" could easily have five states or even more. In contrast, the ratings could only be converted into probability distributions across three states. Otherwise the BN would suggest an accuracy that cannot be justified by the elicitation format. In a second step, single values were converted into conditional probability values. This clearly bears the risk of arbitrariness. To minimize this risk, the auxiliary node "Confidence in experts' estimates" (see Chapter 4.4.1.2) can be used to decide whether the distributions of the expert-based parameters should be flat or distinct.

There are many ways to improve expert-based parameters in BN models (RQ 1) but with regard to extremely short workshop durations (3hours, including translations) and no other chances to meet the experts for additional interviews, the combination of a simplified elicitation and the "outsourcing" of the conversion was very successful. It allowed the development of a fully functioning BN under data scarcity and time constraints. Applying these methods for the parameterization of BNs was presumably more time-efficient (RQ 1.1) than other indirect elicitation formats (although the duration of the elicitation was not explicitly mentioned in the cited publications). However, despite being time-efficient and less onerous, the novel elicitation and conversion method has its limitations. It can only be applied for nodes with one parent node and only to compare the states of the parent node, e.g. management options, with each other. Therefore, this elicitation method is not necessarily a substitute for other elicitation formats but an addition for this particular case of parent-child node-relationship.

4.6.2. Combination and comparison of experts' beliefs

Expert beliefs from more than one expert can either be elicited separately (Catenacci and Giupponi, 2013) or in the form of consensual estimates reached through group discussion (Baran et al., 2006). The first alternative does not require the organizational challenge of convening all experts at one place and one point in time. The latter is known to improve the elicited estimates substantially (Burgman et al., 2011) and to support learning within the group. In the presented case study, it was impossible to invite all experts to WS 2. Therefore, expert beliefs of two small groups were elicited in a workshop setting and the estimates of another expert were elicited during an interview.

The elicitation of several expert beliefs raises the question of how to combine these estimates. Whereas Martin et al. (2005) calculated an unweighted average; Pollino et al. (2007) weighted the elicited conditional probability values according to the experts' own confidence in their estimates. Drew and Perera (2012) criticized the self-assessment of expertise because "expert self-confidence can vary by gender, age and personality type (…)" (Drew and Perera, 2012: 234). They suggested assessing the experts' expertise by asking where, when, and how the experts acquired their knowledge. This can be seen as a call for conducting not only stakeholder analyses but also expert analyses at the very beginning of research projects. An indirect self-assessment, e.g. by asking experts to only fill in conditional probability values they felt "comfortable" with, is the most elegant solution. However, this is only possible if enough experts are involved (e.g. 19 experts as in Catenacci and Giupponi, 2013).

In this case study, the calculation of weighted averages based on self-assessed confidence turned out to be problematic, too. The expert group which gave rather low ratings had the least confidence (Expert group A), whereas the expert group which assigned the highest ratings was most confident (Expert group B). Although the expert groups shared the same opinion on most plant species, the different use of scale led to different probability distributions in the leaf nodes – and the calculation of weighted averages was dominated by the most confident group. However, the self-assessment of confidence gives experts the opportunity to formulate the degree to which they regard their knowledge as certain. It is possible that experts appreciate the possibility to dilute their estimates; especially if they feel uncomfortable with providing probability values (see Chapter 4.6.1). Here, the final solution was to use the self-assessed confidence for the selection of four different conversion tables (see

Chapter 4.4.1.2) and to give different expert opinions as well as differing levels of confidence transparent with two auxiliary variables: “Expert groups” and “Confidence of expert groups”. Such a transparency helps to improve the reliability of expert-based BNs (RQ 1.2).

Most experts involved were very confident, maybe overconfident, in their own estimates but did not expect other experts to have equal expertise. In their perspective, calculating weighted average values “spoiled” their estimates. Therefore, the BN with the “Expert group” node (see Figure 42) was shown during a personal interview with expert C and during WS 3. After having conducted this case study, the author recommends using BNs to compare expert beliefs rather than using combined expert beliefs in a BN. A BN that shows all (conflicting) expert beliefs with an auxiliary node is probably more feasible to facilitate group discussions than averaged values. In addition, a BN that makes differing expert beliefs transparent also conveys the insight that the explanatory power of the model is limited by data and knowledge uncertainty and should not be interpreted as “absolute truth”.

4.6.3. Bayesian Networks and Bayesian Decision Networks

The two small Bayesian Decision Networks (BDNs) were developed as add-ons for the ESS BN (see Chapter 4.3.1). The rankings from the BDNs served as orientation for the experts who applied the ESS BN during WS 3. This might have enhanced the user-friendliness (RQ 2) but also entailed difficulties. There are convincing arguments for and against applying BDNs (RQ 2.1). On the one side, the total expected utility values provided by the decision node were interesting for the workshop participants (see Chapter 4.4.2). On the other side, there is a high risk that these values are accepted as an “ultimate answer”; this is the reason why Cain et al. (2003) decided against applying BDNs in their case study. To avoid this, the BDN results were used in combination with a BN. Due to the broad labels used as states in the ESS BN, its model output is automatically understood as trends or tendencies and not absolute numbers.

This case study shows that BDNs can easily be adapted to various problem fields, even if no monetary costs are involved. For future combined applications of BNs and BDNs, the author recommends an extended introduction to (deterministic) BDN modeling. In alignment with Chapter 4.6.2, it would be useful to develop various BDNs for the estimates of each expert group instead of only developing one BDN based on weighted average values. Having several rankings instead of a single “answer” could encourage the BN model user to iteratively change the probability distribution across different states in the root nodes of the BN to find an optimal combination.

4.7. Conclusion

Drew and Perera (2012) stipulated that the performance of expert-based models should not be compared with data-based models because in most cases expert knowledge substitutes for data that is not available. Therefore, having an expert-based model should rather be compared to not having a model. In this case study, it was the choice between developing an expert-based BN with a high number of deterministic CPTs and building no model at all.

One could question the necessity of a model that solely compares plant species with each other. Why not ask experts directly which plant species are most suitable to mitigate dust weather and provide shade? For simple ratings of the plant-species, each expert might have used different selection criteria. However, by eliciting their estimates on "Plant-specific soil protection", "Plant-specific wind protection", and "Plant-specific dust filter", the experts could reflect on each parameter separately. The added value of the BN was that the experts had a visual causal network as a basis for discussions and that the problem field was broken down into parameters which made it easier to understand and quantify complex cause-effect-relationships.

The truth be told, it is very unlikely that the ESS BN will ever be used again. There are several reasons for this appraisal. For example, no future model user was defined at the very beginning of the research project (with interest and financial capacities to understand and maintain the BN). In addition, the BN modeling process was not an ideal "participatory" process in which the participants get to know each other, start to trust each other and develop a sense of ownership towards the modeling process and the model.

With regard to expert-based Bayesian Network modeling, the following conclusions can be drawn from this case study:

(1) Elicitation and conversion method: Alternative elicitation formats, such as 0-1 and – to +++, can easily be used to elicit expert's estimates on the impact of different management options (or states) of single parent nodes. The elicited estimates can subsequently be converted into conditional probability tables. These alternative elicitation formats were less time-consuming, less fault-prone, and preferred by the experts in comparison to the elicitation of conditional probabilities. The elicitation of numerical values (0-1) allows the conversion into conditional probability values for a higher number of states than fixed elicitation categories (–, +, ++, +++).

(2) Conflicting estimates and different levels of confidence: Auxiliary variables with states that represent expert groups separately are more suitable to compare and discuss conflicting estimates than using the average values of diverging expert beliefs. Auxiliary variables also prove to be useful to show the varying

levels of confidence of different expert groups. This made the uncertainty of the input data, here expert knowledge, very transparent.

(3) Bayesian Decision Networks: The cost-benefit analysis performed by Bayesian Decision Networks can be applied if no monetary costs are involved. Interpreting ecosystem services as “benefits” and irrigation needs as “costs” prove to be very useful for the comparison of different plant species in their ability to mitigate dust weather and to provide shade in oasis towns in NW China.

Apart from new methods of expert elicitation and conversion of estimates into probability values, what has been learnt in the course of this case study? Due to the ever-changing composition of workshop participants, the modeling process focused on knowledge elicitation of each workshop group and knowledge exchange between the workshop groups. The workshop participants learnt from each other by exchanging their domain knowledge in a very structured way. The expert workshops offered a platform to discuss the role of urban and peri-urban vegetation in mitigating dust weather and urban heat stress as well as the provision of ecosystem services in general. Local researchers learnt about BN modeling during the training course in Urumqi in 2014. For the author, the most valuable lessons were taught by the research conditions in Xinjiang; to stay calm in case of unexpected complications, to react with serenity, and to make the best out of it. In the end, great teamwork and good relationships to local partners are the prerequisites to successfully resolve such a case study.

5. Case Study Australia: Ecosystem services of environmental flows in the Murray-Darling Basin[14]

5.1. Introduction

Environmental flows are defined as “quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems“ (Brisbane Declaration, 2007). This definition acknowledges not only the environment as a legitimate water user by itself but also emphasizes that human well-being depends on goods and services of healthy ecosystems. Much of the environmental flow research focuses on the linkages between environmental flows and ecosystem condition, e.g. environmental flow requirements and ecological responses to environmental flows (Arthington et al., 2006; Pahl-Wostl et al., 2013; Poff and Zimmerman, 2010). One approach that could be suitable to analyze the linkages between ecosystem condition and human well-being is the concept of ecosystem services.

Ecosystem services (ESS) are broadly defined as benefits that people obtain from ecosystems (Millennium Ecosystem Assessment, 2005) and can be grouped into provisioning, regulating, cultural, and supporting services. Provisioning services are benefits from the provision of natural resources, such as food, freshwater and timber. Regulating services are benefits from the regulation of ecosystem processes, such as maintenance of hydrological regimes or regulation of local climate. Cultural services are recreational and spiritual benefits of intact ecosystems. Supporting services, such as nutrient cycling and soil formation, are necessary for the provision of all other ecosystem services.

The Economics of Ecosystems and Biodiversity (TEEB) for water and wetlands report 2013 also stipulated that water-related ESS should become an integral part of water resource management (Russi et al., 2013). The difficulty in modeling and managing ESS is the need to first assess and quantify them. In fact, the relationships between environmental flows, ecosystem conditions and ESS are highly uncertain and difficult to quantify (Pahl-Wostl et al., 2013). Probabilistic models, such as Bayesian Networks (BNs), provide the opportunity to explicitly express this uncertainty. Therefore BNs are increasingly used to model ESS (Landuyt et al., 2013) and to support environmental flow management (Shenton et al., 2014).

This case study is the result of a three-month research stay in Australia. The task was to identify the broad range of services provided by ecosystems in the Murray-Darling

[14] Parts of this chapter, namely text passages of Chapter 5.1, are extracted from the author’s contributions to Frank et al. (2014b).

Basin (MDB), and to develop a BN that shows the links between environmental flows, the ecosystem condition and ESS.

This chapter briefly introduces how environmental flows are managed in the MDB (Chapter 5.1.1) and which ESS are provided by some of the Basin's Ramsar sites (Chapter 5.1.2).

5.1.1. Environmental flow management in the Murray-Darling Basin

The Murray-Darling Basin (MDB), named after the Murray River and the Darling River, comprises about one-seventh of Australia's land mass and lies in the four states of Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA), and the Australian Capital Territory (ACT) (Murray-Darling Basin Authority, n.d.).

The Murray-Darling Basin Authority (MDBA), established by the Water Act 2007, is responsible for basin-wide water resources management and planning. With regard to managing environmental flows, the MDBA needs (1) to identify the environmental flow requirements of the Basin, and (2) to set sustainable diversion limits for the amount of water that can be taken for industry, agriculture and other consumptive water uses accordingly (Murray-Darling Basin Authority, 2011). These environmentally sustainable levels of take (ESLT) should leave enough water to the environment to sustain ecosystems and to ensure the provision of ESS. The Basin Plan 2012 was passed to establish and legally enforce environmentally sustainable levels of take for each catchment and the whole Basin.

The Basin Plan also aims at giving effect to international agreements such as the Convention on Wetlands or the Ramsar Convention (1971). This treaty calls for a "wise use" of all wetlands and requests the member countries to maintain the "ecological character" of Wetlands of International Importance, so-called Ramsar sites. By now, the definitions used for "wise use" and "ecological character" have been aligned with the more widely used terms of the ESS concept (Ramsar, 2005). Therefore, the ESS concept is widely used in Australia to manage environmental flows and to implement the Ramsar Convention.

In 2012, the MDBA commissioned a research project on ecological and economic benefits of environmental flows in the Murray-Darling Basin (CSIRO, 2012). The "CSIRO Multiple Benefits of the Basin Plan Project" identified and quantified ESS expected to arise from recovering more water, namely 2800 GL/year, for the environment in the Basin. This short-term research project solely focused on 10 rather broad provisioning, regulating, and cultural services (CSIRO, 2012: 9).

Figure 51: Map of the Murray-Darling Basin and its Ramsar sites (Murray-Darling Basin Authority, n.d.).

5.1.2. Ecosystem services in the Murray-Darling Basin

As the "Multiple Benefits" project analyzed a very limited number of ESS, the first task was to identify more Basin-specific ESS by reading through all available Ecological Character Descriptions (ECDs) of the Ramsar sites in the MDB. As the "ecological character" of Ramsar sites is defined as "the combination of ecosystem components, processes and services that characterize the wetland at any given point of time" (Ramsar, 2005), the ECDs provide a good overview of water-related and wetland ESS in the MDB.

At that time, eleven of the 16 existing Ramsar sites in the MDB were described in ECDs. Ten of these ECDs used the ESS concept to describe the ecological character of the wetlands. Therefore, the ECDs of the ten Ramsar sites were screened for ESS to be included in the BN on ecosystem services in the Murray Darling Basin, the "MDB BN".

The ten ECDs of Banrock Station Wetland Complex, Barmah Forest, Blue Lake, Currawinya Lakes, Ginini Flats Wetland Complex, Hattah-Kulkyne Lakes, Kerang Wetlands, Macquarie Marshes, Paroo River Wetlands, and Riverland are not standardized (see Figure 51 for locations). The authors of these reports – working for commissioned environmental consultancies and state departments – used different terms to describe the same ESS. In addition, some provisioning and regulating services, such as fresh water supply or sediment trapping, are most likely provided by all Ramsar sites but not mentioned in all ECDs. Only few provisioning services, such as salt harvesting, and most cultural services are site-specific and probably cannot be found in all Ramsar sites (see Table 23 and Table 24).

Table 23: Provisioning and regulating services mentioned in 10 Ecological Character Descriptions (ECDs).

	ESS mentioned in the ECDs of Ramsar sites									
Ecosystem services	R1[1]	R2[2]	R3[3]	R4[4]	R5[5]	R6[6]	R7[7]	R8[8]	R9[9]	R10[10]
Provisioning services										
Apiculture		x							x	
(Biochemical products and genetic resources)*				x				x		
Cattle grazing		x	x				x		x	x
Firewood collecting		x								
Fresh water supply			x	x	x	x	x	x	x	x
Fresh water storage (emergency stock)						x	x	x		
Salt harvesting							x			
Timber production		x								
Regulating services										
Biological control of pests and diseases				x				x		
Carbon sequestration	x	x	x	x	x					x
Erosion protection					x			x		
Groundwater recharge		x					x			
Maintenance of hydrological regimes (incl. flood control)	x	x	x	x	x	x	x	x	x	x
Maintenance of local climate				x				x		
(Reduction in fire intensity when wet)**								x		
Regulation of water temperature			x							
Sediment trapping/retention			x	x		x		x		x
Salinity water disposal							x			x
Water quality maintenance (incl. pollution control, detoxification, and sewerage disposal)				x	x		x	x		x

*included as floating node in MDB BN, **not included in MDB BN

[1]Banrock Station Wetland Complex (Butcher et al., 2009), [2]Barmah Forest (Hale and Butcher, 2011), [3]Blue Lake (Department of Environment and Climate Change NSW, 2008), [4]Currawinya Lakes (Fisk, 2009), [5]Ginini Flats Wetland Complex (Wild et al., 2010), [6]Hattah-Kulkyne Lakes (Butcher and Hale, 2011), [7]Kerang Wetlands (Department of Sustainability and Environment VIC, 2010), [8]Macquarie Marshes (Office of Environment and Heritage NSW, 2012), [9]Paroo River Wetlands (Kingsford and Lee, 2010), [10]Riverland (Newall et al., 2008).

Table 24: Cultural services mentioned in 10 Ecological Character Descriptions (ECDs).

	ESS mentioned in the ECDs of Ramsar sites**									
Ecosystem services	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Aboriginal cultural heritage	x	x				x	x	x	x	x
Aboriginal hearths	x									
Aboriginal scar trees	x	x								x
Burial sites		x								x
Dreaming tracks									x	
Ground stone artefacts	x	x								
Mounds		x								
Shell middens	x	x								x
Stone tools	x									
Aboriginal heritage – not specified						x	x	x		
Educational value (conservation education)	x	x	x	x		x	x	x	x	x
European heritage (historic relics)	x	x	x						x	x
Scenic values/Aesthetic amenity/ Appreciation of natural features		x		x		x	x	x		x
(Scientific research)*	x	x	x	x			x	x	x	x
Sense of place/Spiritual and inspirational		x		x	x			x		
Recreation and (Eco-)Tourism	x	x	x	x	x	x	x	x	x	x
Alpine sports (rock/ice climbing, skiing)			x		x		x			
Camping				x		x	x		x	x
Cycling/Driving/Horse riding	x	x				x				
Hunting	x	x					x			
Nature observation (incl. bushwalking and bird watching)		x	x	x	x	x			x	
Recreational fishing/yabbying (incl. bait collecting)	x	x		x		x	x	x	x	x
Tourism (touring)		x		x		x			x	
Water sports (swimming, scuba diving, wind surfing, boating, house-boating, canoeing)			x	x		x				x

*included as floating node in MDB BN

**for names of Ramsar sites and references for ecological character descriptions see footnote below Table 23.

5.2. Model development

The MDB BN was developed in close collaboration with Carmel A. Pollino who hosted the author during the research stay at CSIRO (Land and Water) in Canberra, Australia. This chapter first describes the structure of the four sub-networks and highlights how these sub-networks are linked together to form the final network structure (Chapter 5.2.1). It also presents how the CPTs were populated with the help of expert knowledge, information from the ECDs, and equations (Chapter 5.2.2).

All BNs presented in this chapter have uniform probability distributions in the root nodes. The model-user can compare scenarios with the root nodes by setting the probability of a certain state to 100% or by changing the probability distributions in their probability tables (PTs).

5.2.1. Development of the network structure

5.2.1.1. Sub-network on ecosystem condition

Supporting services, such as nutrient cycling and soil formation, are necessary for the provision of all other ecosystem services. Here, the concept of supporting services is replaced by the term "ecosystem condition". Whether the ecosystem is in a poor or healthy condition depends on whether it performs certain functions ("Function components"), exhibits biodiversity, and supports ecological connectivity ("Structure components"). From bottom to top, the sub-network suggests that the ecosystem condition depends on its structural and functional components, all depicted in green (Figure 52).

In which state these components are hinges on how much water is available for a certain period of time. The impact of low or high water availability is very different whether a condition remains unchanged for one year or up to five or ten years. The water availability is influenced by annual water supply, environmental flows and the duration. This way, the BN highlights what difference environmental flows can make if the annual water supply was low for a certain period of time. As a healthy ecosystem is the starting point for the provision of most ESS, the sub-network on ecosystem condition serves as input for the sub-networks on provisioning, regulating, and cultural services (see Figure 53 and Figure 54).

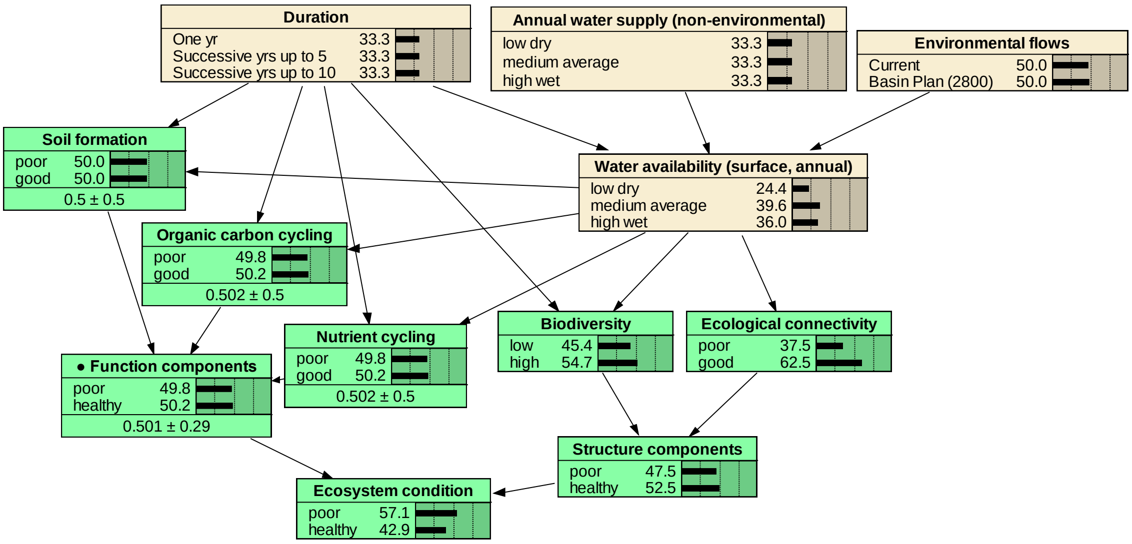


Figure 52: Sub-network on ecosystem condition.

5.2.1.2. Sub-network on provisioning services

The sub-network on ecosystem condition, here visualized with green circles, serves as input for the sub-network on provisioning services which is depicted in blue (Figure 53). The sub-network includes eight provisioning services and their so-called summary node "Provisioning services" (see Chapter 5.2.2.3).

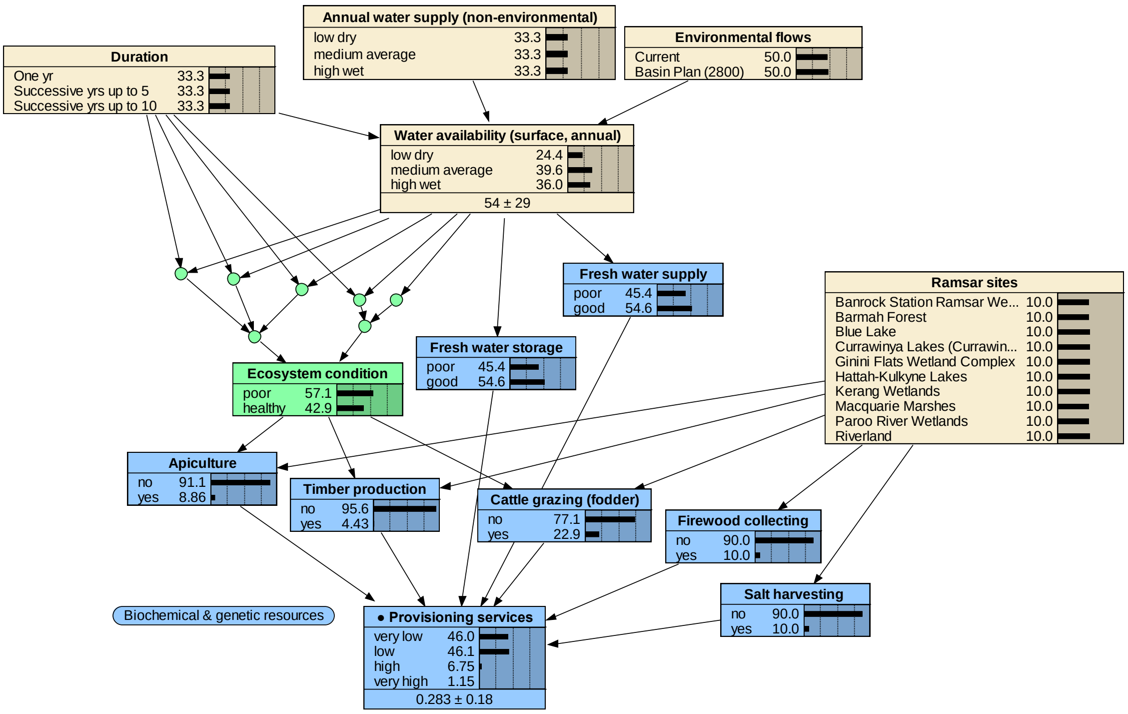


Figure 53: Sub-network on provisioning services.

The sub-network indicates that two ESS, namely “Fresh water supply” and “Fresh water storage”, directly depend on “Water availability”. Three ESS, among others “Apiculture”, depend on a healthy “Ecosystem condition”. The remaining two ESS, “Firewood collecting” and “Salt harvesting”, are rather independent of water availability and the ecosystem condition. To reduce the number of links in the MDB BN, the “Ramsar sites” node is solely linked to site-specific ESS that only exist in few Ramsar sites, such as “Salt harvesting”. “Fresh water supply” and “Fresh water storage” are most likely provided by all Ramsar sites and therefore not connected to the “Ramsar sites” node. Some ECDs mention the potential existence of “Biochemical products and genetic resources” for medicine (Table 23). As this cannot be quantified, it is solely indicated by a floating node.

Ramsar sites are usually not used for irrigated agriculture. This is why only “Cattle grazing” is included in the sub-network on provisioning services. With regard to basin-wide agricultural production, increasing environmental flows in the MDB would require a shift from irrigated agricultural production towards dryland agricultural production in the Basin in the long-term (CSIRO, 2012).

5.2.1.3. Sub-network on regulating services

The sub-network on regulating services also builds on the sub-network on ecosystem condition. The sub-network includes ten regulating services and their summary node “Regulating services”– all depicted in yellow. Seven of these services depend on a healthy “Ecosystem condition”, whereas “Groundwater recharge” is solely dependent on “Water availability” (Figure 54, on top).

Except for “Salinity water disposal”, all regulating services are not site-specific but presumably provided by all Ramsar sites. The node “Maintenance of hydrological regimes” is connected to the “Ramsar sites” node to indicate in which Ramsar sites this service has been modified by anthropogenic influences.

5.2.1.4. Sub-network on cultural services

The sub-network on cultural services is very complex (Figure 54, at the bottom). It consists of 22 cultural services and their summary nodes “Recreation & (Eco-) Tourism”, “Aboriginal cultural heritage”, and “Cultural services” – all depicted in purple. This sub-network is a first attempt to define the linkages between cultural services, water availability, and a healthy ecosystem condition which are very difficult to quantify.

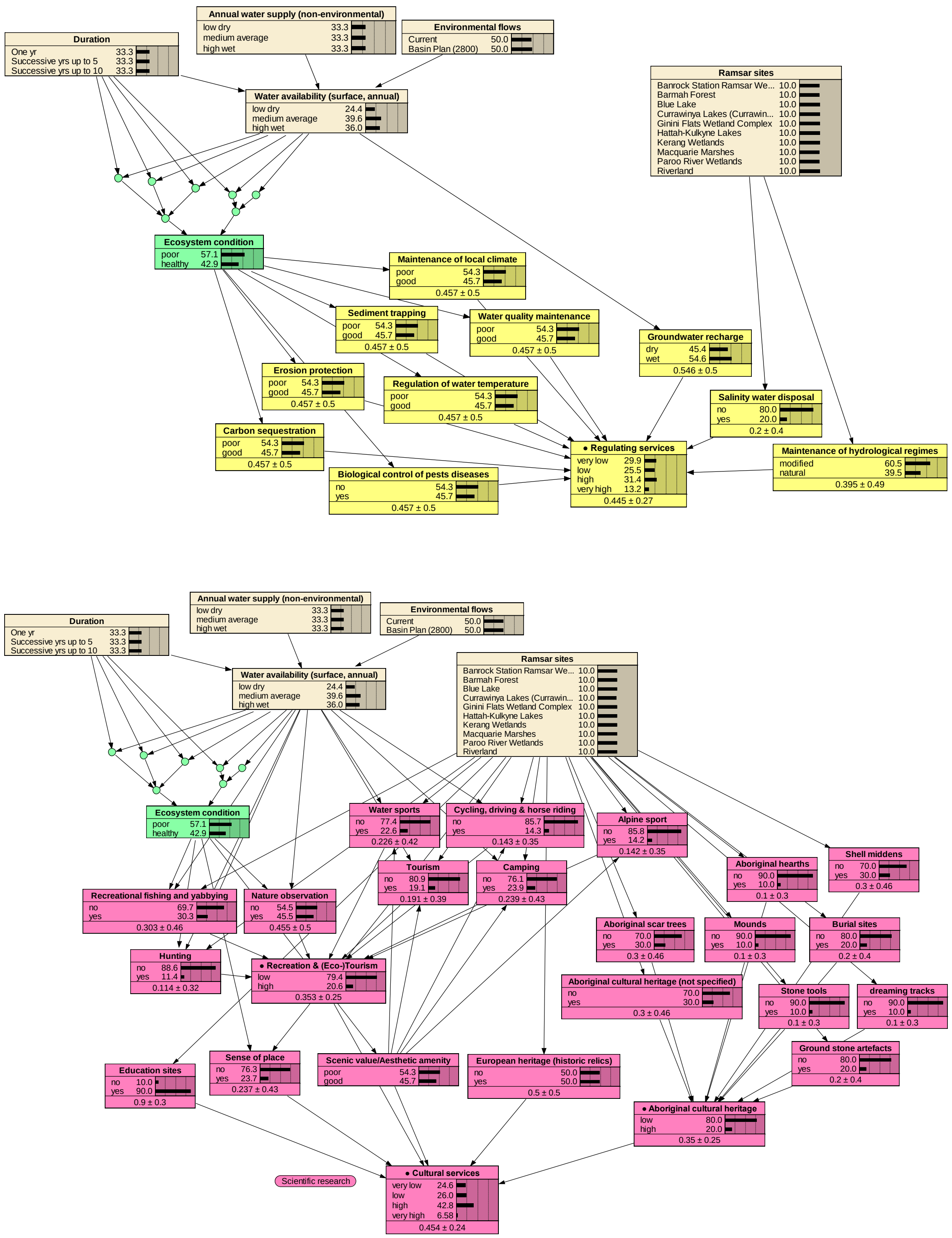


Figure 54: Sub-network on regulating services (on top) and sub-network on cultural services (at the bottom).

In this sub-network, the node “Education sites” and all nodes related to cultural heritage are not dependent on “Water availability” or “Ecosystem condition”. However, they are site-specific and therefore connected to the “Ramsar sites” node. Most nodes related to “Recreation & (Eco-) Tourism” either depend on a healthy “Ecosystem condition”, e.g. “Nature observation”, or on “Water availability”, e.g.

"Water sports". Some activities, such as "Camping", are presumably also influenced by the "Scenic value/Aesthetic amenity"; while other activities, such as "Hunting", could probably be done in a less aesthetic landscape.

5.2.1.5. Final network structure

The combined BN consists of 63 nodes[15], 122 links, and 8176 probability values. Out of all ESS mentioned in the 10 ECDs, the MDB BN includes 7 provisioning, 10 regulating (see Table 23), and 21 cultural services (see Table 24). The four root nodes can be used to analyze the impact of annual water supply on the ecosystem condition and all ESS simultaneously (Figure 55). For example, the MDB BN can be used to see the impact of low water availability for different periods of time and to show how environmental flows can help to sustain a healthy ecosystem condition and to provide ESS in case of low water availability. As the MDB BN models all ESS for all Ramsar sites, it is possible to compare different Ramsar sites with each other.

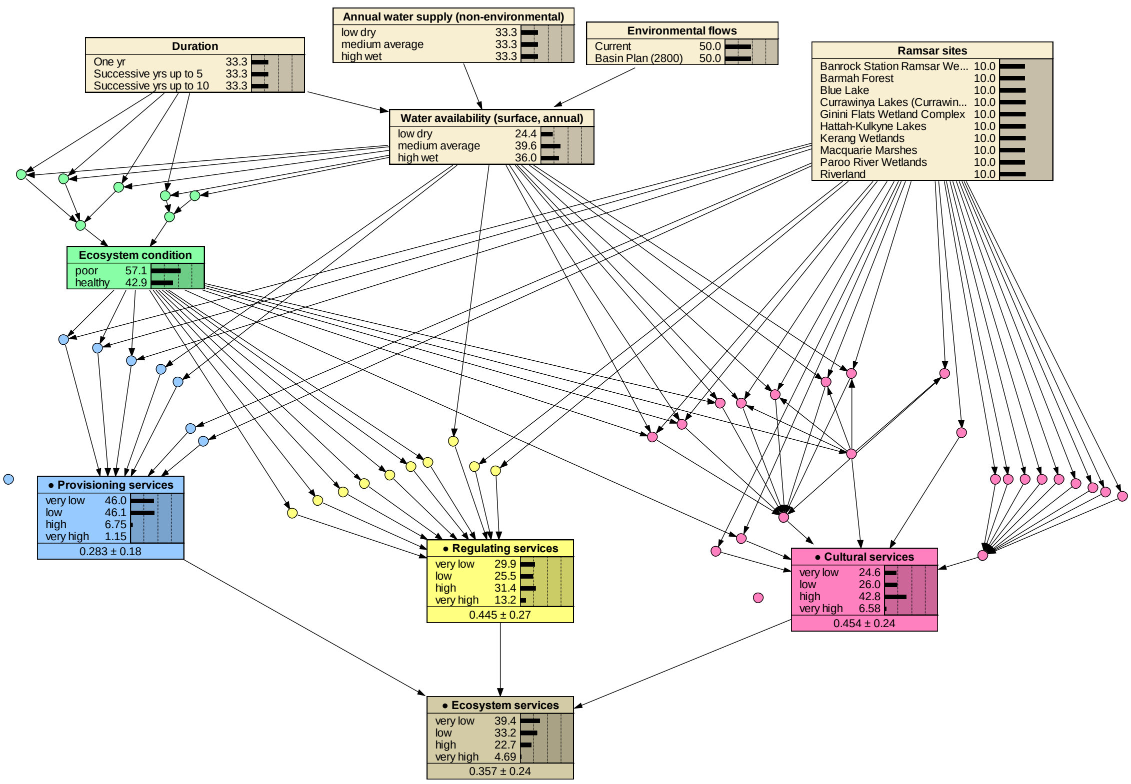


Figure 55: Simplified version of the MDB BN.

[15] Five of these nodes are hidden as they are only used for the equations (see Chapter 5.2.2.3).

However, the size of the MDB BN has become too large. The combined BN can only be shown in a simplified version that depicts most variables as circles[16] (Figure 55). It would also be too large to be presented to stakeholders, such as the MDBA that commissioned the CSIRO Multiple Benefits project in the first place. To address this shortfall, the author developed a nested BN with different BN software (see Chapter 5.3).

[16] Netica ► Right-click on node ► Style ► Circle.

5.2.2. Model parameterization

To parameterize the MDB BN, different data and knowledge sources were used. For the linkages between annual water supply, environmental flows, water availability, ecosystem condition, and ESS that are provided by all wetlands, expert judgments were elicited from Carmel A. Pollino, henceforth referred to as the expert. For all variables that are linked to the “Ramsar sites” node, information from ecological character descriptions (ECDs) was used. For all summary nodes, the conditional probability tables (CPTs) were built from equations.

5.2.2.1. Model parameterization with data

The information on which ecosystem services (ESS) can be found in each Ramsar sites was derived from ten ecological character descriptions (ECDs). Some ESS are just not mentioned in all ECDs but most likely provided by all Ramsar sites (see Table 23). In these cases, the ESS are not linked to the Ramsar sites node to reduce the number of links to keep the CPTs manageable. Other ESS, such as timber production and salt harvesting, cannot be found in all wetlands. Only in these cases, the variables are linked to the “Ramsar sites” node and the CPTs were populated with the information provided by the ECDs.

Here, three examples show how information from the ECDs was used to fill in the CPTs. The first example is “Timber production”. This variable depends on the Ramsar site and the ecosystem condition. As timber is solely produced in Barmah Forest, the conditional probability values are 100% “no” for all other Ramsar sites – no matter which ecosystem condition prevails (Table 25). In Barmah Forest, the ecosystem condition strongly influences the timber production. This is why the 90:10 ratio reverses if the ecosystem condition changes from poor to healthy and vice versa.

Table 25: Conditional probability table of “Timber production”.

region	ecosystem_condition	no	yes
Banrock Station Ramsar Wetland ...	poor	100	0
Banrock Station Ramsar Wetland ...	healthy	100	0
Barmah Forest	poor	90	10
Barmah Forest	healthy	10	90
Blue Lake	poor	100	0
Blue Lake	healthy	100	0
Currawinya Lakes (Currawinya Nati...	poor	100	0
Currawinya Lakes (Currawinya Nati...	healthy	100	0
Ginini Flats Wetland Complex	poor	100	0
Ginini Flats Wetland Complex	healthy	100	0
Hattah-Kulkyne Lakes	poor	100	0
Hattah-Kulkyne Lakes	healthy	100	0
Kerang Wetlands	poor	100	0
Kerang Wetlands	healthy	100	0
Macquarie Marshes	poor	100	0
Macquarie Marshes	healthy	100	0
Paroo River Wetlands	poor	100	0
Paroo River Wetlands	healthy	100	0
Riverland	poor	100	0
Riverland	healthy	100	0

The second example is “Water sports”. The conditional probability values in each row result from both expert judgments and information in the ECDs. To fill in this large CPT, the expert used simple rules of thumb. For example, “If the water availability is low, it is impossible to do water sports”. With increasing water availability and rising scenic value, the probability of water sports being practiced increases – but only in these Ramsar sites for which the possibility for water sports is mentioned in the ECDs (Table 26).

Table 26: Conditional probability table of “Water sports”.

Water availability (Surface, Ann...	Scenic value/Aesthetic amenity	Ramsar sites	no	yes
low dry	poor	Banrock Station Ramsar Wetland ...	100	0
low dry	poor	Barmah Forest	100	0
low dry	poor	Blue Lake	100	0
low dry	poor	Currawinya Lakes (Currawinya Nati...	100	0
low dry	poor	Ginini Flats Wetland Complex	100	0
low dry	poor	Hattah-Kulkyne Lakes	100	0
low dry	poor	Kerang Wetlands	100	0
low dry	poor	Macquarie Marshes	100	0
low dry	poor	Paroo River Wetlands	100	0
low dry	poor	Riverland	100	0
low dry	good	Banrock Station Ramsar Wetland ...	100	0
low dry	good	Barmah Forest	100	0
low dry	good	Blue Lake	100	0
low dry	good	Currawinya Lakes (Currawinya Nati...	100	0
low dry	good	Ginini Flats Wetland Complex	100	0
low dry	good	Hattah-Kulkyne Lakes	100	0
low dry	good	Kerang Wetlands	100	0
low dry	good	Macquarie Marshes	100	0
low dry	good	Paroo River Wetlands	100	0
low dry	good	Riverland	100	0
medium average	poor	Banrock Station Ramsar Wetland ...	100	0
medium average	poor	Barmah Forest	100	0
medium average	poor	Blue Lake	80	20
medium average	poor	Currawinya Lakes (Currawinya Nati...	80	20
medium average	poor	Ginini Flats Wetland Complex	100	0
medium average	poor	Hattah-Kulkyne Lakes	80	20
medium average	poor	Kerang Wetlands	100	0
medium average	poor	Macquarie Marshes	100	0
medium average	poor	Paroo River Wetlands	100	0
medium average	poor	Riverland	80	20
medium average	good	Banrock Station Ramsar Wetland ...	100	0
medium average	good	Barmah Forest	100	0
medium average	good	Blue Lake	20	80
medium average	good	Currawinya Lakes (Currawinya Nati...	20	80
medium average	good	Ginini Flats Wetland Complex	100	0
medium average	good	Hattah-Kulkyne Lakes	20	80
medium average	good	Kerang Wetlands	100	0
medium average	good	Macquarie Marshes	100	0
medium average	good	Paroo River Wetlands	100	0
medium average	good	Riverland	20	80
high wet	poor	Banrock Station Ramsar Wetland ...	100	0
high wet	poor	Barmah Forest	100	0
high wet	poor	Blue Lake	10	90
high wet	poor	Currawinya Lakes (Currawinya Nati...	10	90
high wet	poor	Ginini Flats Wetland Complex	100	0
high wet	poor	Hattah-Kulkyne Lakes	10	90
high wet	poor	Kerang Wetlands	100	0
high wet	poor	Macquarie Marshes	100	0
high wet	poor	Paroo River Wetlands	100	0
high wet	poor	Riverland	10	90
high wet	good	Banrock Station Ramsar Wetland ...	100	0
high wet	good	Barmah Forest	100	0
high wet	good	Blue Lake	0	100
high wet	good	Currawinya Lakes (Currawinya Nati...	0	100
high wet	good	Ginini Flats Wetland Complex	100	0
high wet	good	Hattah-Kulkyne Lakes	0	100
high wet	good	Kerang Wetlands	100	0
high wet	good	Macquarie Marshes	100	0
high wet	good	Paroo River Wetlands	100	0
high wet	good	Riverland	0	100

The third example is “Aboriginal scar trees”. All variables which have “Ramsar site” as only parent node have deterministic CPTs – either the ESS is mentioned in an ECD or not. Aboriginal scar trees are mentioned in three ECDs and are most likely not existent in the others. Therefore, 100% “yes” is assigned to these three Ramsar sites and 100% “no” is assigned to the other sites (Table 27).

Table 27: Deterministic conditional probability table of "Aboriginal scar trees".

Ramsar sites	Aboriginal scar trees
Banrock Station Ramsar Wetland ...	yes
Barmah Forest	yes
Blue Lake	no
Currawinya Lakes (Currawinya Nati...	no
Ginini Flats Wetland Complex	no
Hattah-Kulkyne Lakes	no
Kerang Wetlands	no
Macquarie Marshes	no
Paroo River Wetlands	no
Riverland	yes

5.2.2.2. Model parameterization with expert knowledge

Most CPTs were directly elicited from Carmel A. Pollino who is an expert in the fields of environmental flow management and BN modeling. Whereas the quantification of some relationships required her specific expertise, other relationships could be filled in by logic reasoning and were solely reviewed by her. For example, the quantification of the relationship between water availability, duration of water availability, and the three function components required expert knowledge. The CPT of "Organic carbon cycling" reflects how an ecosystem can perform its functions as long as the water availability is not too low and not too high. In one year with high water availability, the ecosystem is still functioning well but if this high water availability persists for more than 5 years it affects ecosystem functions just as low water availability (Table 28).

Table 28: Conditional probability table of "Organic carbon cycling".

water_availability	Duration	poor	good
low dry	One yr	70	30
low dry	Successive yrs up to 5	90	10
low dry	Successive yrs up to 10	90	10
medium average	One yr	20	80
medium average	Successive yrs up to 5	20	80
medium average	Successive yrs up to 10	20	80
high wet	One yr	10	90
high wet	Successive yrs up to 5	70	30
high wet	Successive yrs up to 10	90	10

In contrast, the CPT of "Alpine sport" being performed in the Ramsar sites under conditions of poor and good "Scenic value/Aesthetic amenity" is highly subjective. These CPTs were populated with the help of ECDs ("Is alpine sports possible in this Ramsar site?") and generic qualitative assumptions by the author ("How could the scenic value influence the willingness to perform alpine sports?") – and were solely revised by the expert. The "Scenic value" itself depends on the "Ecosystem condition" – if the ecosystem condition is healthy, the scenic value is good with an 80% probability. The CPT of "Scenic value" is used to express that healthy ecosystem conditions do not necessarily lead to a high scenic value.

5.2.2.3. Model parameterization with equations

There are seven so-called summary nodes in the MDB BN (●). Summary nodes are intermediate variables that summarize the impact of all parent nodes – here with the help of simple equations. For all these nodes, the CPTs were built with equations that equally weight the incoming parent nodes (see Chapter 2.2.2). The application of equations allowed the use of more than three states and parent nodes. For example, the leaf nodes “Ecosystem services” and its parent nodes “Provisioning services”, “Regulating services”, and “Cultural services” could have four states each. The resultant CPT of the leaf node “Ecosystem services” consists of 256 conditional probability values and would have been too complex for expert elicitation. Instead, the following equation was used:

ecosystem_services (cultural_services2, provisioning_services2,
regulating_services2) =
(cultural_services2+provisioning_services2+regulating_services2)/9

This way, the MDB BN treats all ESS as equally important. The possibility to have more than three parent nodes allowed the summary node “Aboriginal cultural heritage” to summarize the input of 9 parent nodes, and the node “Regulating services” to process 10 parent nodes.

The nodes “Aboriginal cultural heritage”, “Recreation & (Eco-) Tourism”, “Provisioning services”, “Regulating services”, and “Cultural services” exist two times in the MDB BN. One is needed as continuous summary node; the other as discrete node which serves as input to the summary nodes “Cultural services” and “Ecosystem services”. To avoid confusion, the extra nodes are hidden below their counterparts (compare Chapter 2.2.2 and Chapter 4.2.3.2).

5.3. Add-on: Nested MDB BN

At the end of the research stay in Australia, the network structure of the MDB BN had become too large to be presented to stakeholders or scientists at conferences. To improve its manageability, the MDB BN was rebuilt using GeNIe 2.0 (https://dslpitt.org/genie/), a free software tool developed at the University of Pittsburgh. Two versions of the MDB BN were developed using GeNIe – one as "normal" BN (see Figure 56) and one as nested BN (see Figure 57). The nested MDB BN consists of a main model and five sub-models. The software either shows the main model (Figure 57) or a sub-model (Figure 58) at a time.

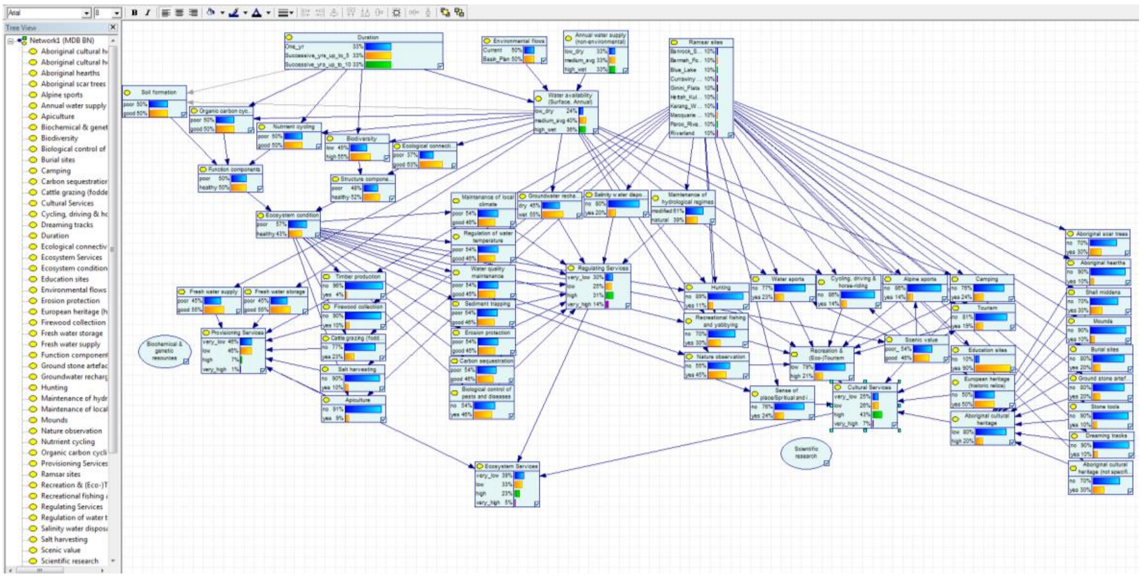


Figure 56: Screenshot of MDB BN in GeNIe.

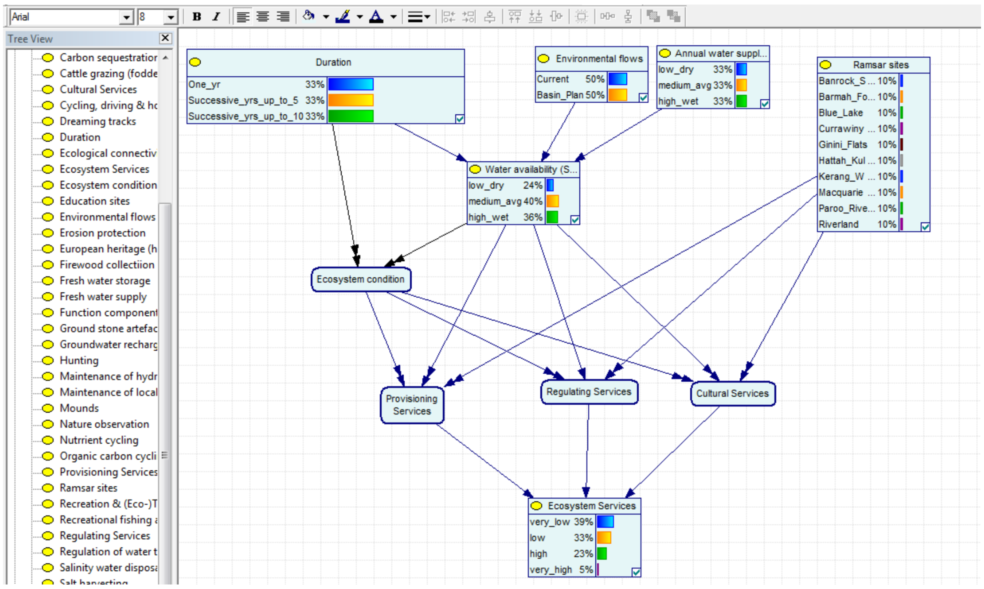


Figure 57: Screenshot of main model of nested MDB BN.

All variables that belong to the sub-models “Ecosystem condition”, “Provisioning services”, “Regulating services”, and “Cultural services” are hidden when the main model is shown (Figure 57). Sub-models are denoted by blue rounded squares. Sub-models are positioned at another “level” but can be opened by clicking on the sub-models listed on the left. It is also possible to build sub-models within sub-models. For example, the sub-model “Aboriginal cultural heritage” within the sub-model on “Cultural services” (Figure 58).

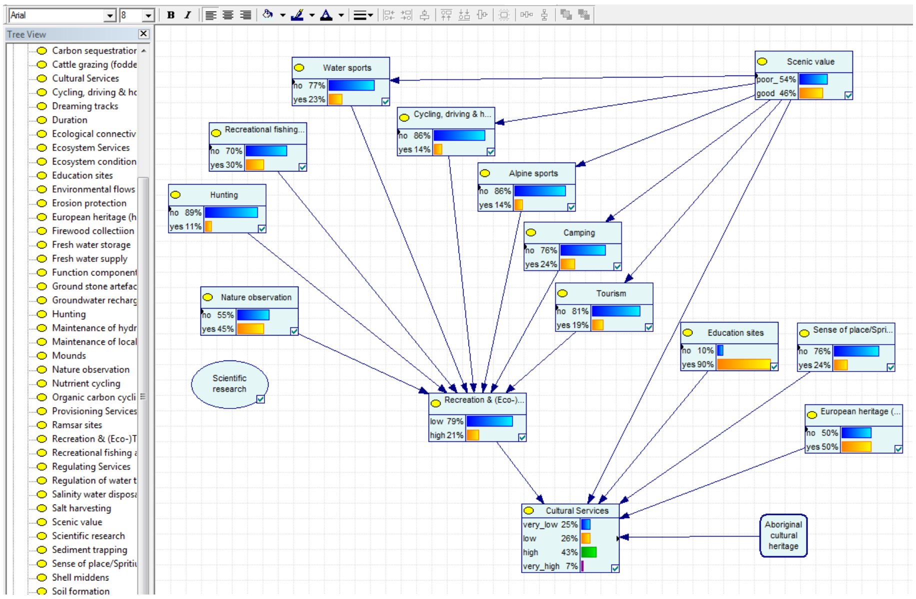


Figure 58: Screenshot of sub-model on cultural services.

While rebuilding the MDB BN, some differences between Netica and GeNIe stood out. For example, in Netica, single nodes of a BN can be quantified with the help of equations, whereas in GeNIe, either all nodes use equations or none. To solve this software problem, all CPTs that were built from equations in Netica were copied into the BN in GeNIe. A minor difference is that the CPTs are organized the other way around. CPTs in Netica are row-wise, CPTs in GeNIe are column-wise (Figure 59).

Structure components	function_components	poor	healthy
poor	poor	100	0
poor	healthy	50	50
healthy	poor	100	0
healthy	healthy	0	100

Structure com...	poor		healthy	
Function comp...	poor	healthy	poor	healthy
poor	1	0.5	1	0
healthy	0	0.5	0	1

Figure 59: Conditional probability tables in Netica and GeNIe.
At the top, conditional probability table of “Ecosystem condition” in Netica; at the bottom, the same conditional probability table in GeNIe.

5.4. Discussion

Although BNs could easily be used to model several ESS simultaneously, most BN applications focus on one or two ESS only (Landuyt et al., 2013). In this case study, a BN was developed to quantify the relationships between environmental flows, water availability, ecosystem condition and 38 provisioning, regulating and cultural services. These 38 ESS have a high number of incoming links from their parent nodes "Ramsar sites" (26 links), "Ecosystem condition" (15 links), and "Water availability" (10 links). This makes it difficult to present the final network.

There are two ways how to make large BNs more user-friendly or intelligible to those who view and use the model (RQ 2). One solution is to present simplified versions of large BNs by visualizing some of the nodes as circles or labeled boxes (e.g. Kumar et al., 2012). This brings the attention to the more important nodes but also leads to a loss of information. Another solution is to create a nested BN – a main model with several sub-models (e.g. Penman et al., 2011). With respect to model application and user-friendliness, there is a trade-off between clarity and accurate visualization of causal relationships. Whereas a "normal" BN confronts the model user with the whole network structure by showing all links and nodes at a time, the software GeNIe either shows the main model or a sub-model of the nested BNs.

The visualization of causal links is limited in nested BNs. Links between nodes in the main model and a sub-model are not represented by single links. Instead, all inter-model links are summarized into the main model in one link pointing to the sub-model (see Figure 57). In the sub-model, incoming inter-model links are solely depicted by little triangles on the left side of the node; outgoing links are shown by triangles on the right side of the node (Figure 58). The cursor of the computer mouse can be used to display a list with further information of the origin and the destination of these links. Having less nodes and links to look at is presumably less confusing for the model user. However, the visualization of causal relationships with triangles is not as expressive as causal links. The model user needs to switch between main model and sub-models to understand how the whole model is connected.

Thus, developing BNs with Netica and nested BNs with GeNIe entails advantages and disadvantages for the development and application of large BNs (RQ 2.2). Except for minor differences in the layout of CPTs, developing the MDB BN in Netica and GeNIe was quite similar. Only the possibility of building some CPTs from equations while deriving others from different sources was missing in GeNIe (see Chapter 5.3). However, GeNIe offers many other opportunities that were not exhausted in this case study. For example, GeNIe can be used to develop Object-Oriented Bayesian Networks (OOBNs) or Dynamic Bayesian Networks (DBNs). With more data on each Ramsar site, the nested MDB BN could be rebuild as an OOBN, with ten identical "objects" for the Ramsar sites (see Chapter 2.5.2).

5.5. Conclusion

Chen and Pollino (2012) highlighted that the possibility to iteratively update BNs with new data gives BNs a longer lifespan than most other models. As the research stay in Australia was limited to three months, the MDB BN represents a body of knowledge that was easily accessible and processible in a very short time. At the end of the research stay, the MDB BN was fully parameterized with the help of estimates of one expert, information derived from ten ecological character descriptions, and seven equations. The MDB BN can therefore be regarded as "alpha-level model" (Marcot et al., 2006) or "first generation model" (Amstrup et al., 2008). The 8128 probability values of the MDB BN could be replaced or complemented with additional data or expert and stakeholder knowledge in the future.

This thesis highly benefited from the research stay in Australia. The exchange with Australian BN modelers improved the expert-based BN which was developed in NW China (see Chapter 4). In addition revisiting the "Multiple Benefits" project provided the opportunity to compare BN software tools with respect to user-friendliness of large BNs. In contrast to the BNs developed in the case study Northwest China, the MDB BN is in the "good hands" of experienced modelers. Due to their expertise in BN modeling and their interest in environmental flows and ecosystem services in the Murray-Darling Basin in general, there is a high chance that the results of this case study will be of use in the future.

6. Conclusion

The case studies conducted in Northwest China and Australia aimed at further developing expert-based Bayesian Network modeling techniques. Due to differing project time, the depth of study and the subsequent contributions to science and environmental management vary between the case studies.

6.1. Scientific contribution

The scientific contribution of the case study in Northwest China consists of the design and application of an elicitation and conversion method that complements existing expert elicitation techniques. The key characteristics of this method are its time-efficiency and the approach to use different conversion tables based on varying levels of confidence. In addition, this monograph provides the opportunity to share all the intricacies faced during the challenging case study in Northwest China. Fragmented or complicated participatory processes, e.g. with a high fluctuation of participants, are rarely published; yet they provide a notion of how participatory processes can take unexpected turns and how to find a way to successfully complete them nonetheless.

The scientific contribution of the case study in Australia consists of the development of a “first-generation” Bayesian Network on ecosystem services of environmental flows in the Murray-Darling Basin. Due to the short project time, most conditional probability tables were filled by an expert; however, they could be complemented by data in the future. This case study also broaches the issue of user-friendliness of large Bayesian Networks and nested Bayesian Networks. The short comparison neither advocates a Bayesian Network type nor software; it rather highlights the need to consider the applicability and presentation clarity of large models.

6.2. Contribution for environmental management

The real-world purpose of the case study in Northwest China was to support and inform local vegetation managers and planners. It is difficult to assess the contribution of this case study for local environmental management. The high fluctuations of workshop participants reduced the perceived “ownership” of the modeling process and model results. Nevertheless, each workshop provided a platform for discussion and mutual learning. As in many other participatory Bayesian Network applications, the knowledge exchange during the modeling process was at least as valuable to the workshop participants as model results.

References

Aguilera, P., Fernández, A., Fernández, R., Rumí, R., Salmerón, A., 2011. Bayesian networks in environmental modelling. Environmental Modelling & Software 26 (12), 1376–1388. DOI: 10.1016/j.envsoft.2011.06.004.

Alcoforado, M.-J., Matzarakis, A., 2010. Planning with urban climate in different climatic zones. Geographicalia 57, 5–39.

Allan, J.D., Yuan, L.L., Black, P., Stockton, T.O., Davies, P.E., Magierowski, R.H., Read, S.M., 2012. Investigating the relationships between environmental stressors and stream condition using Bayesian belief networks. Freshwater Biology 57, 58–73. DOI: 10.1111/j.1365-2427.2011.02683.x.

Amstrup, S.C., Marcot, B.G., Douglas, D.C., 2008. A Bayesian Network Modeling Approach to Forecasting the 21st Century Worldwide Status of Polar Bears, in: DeWeaver, E.T., Bitz, C.M., Tremblay, L.-B. (Eds.), Arctic sea ice decline. Observations, projections, mechanisms, and implications. American Geophysical Union, Washington, DC, 213–268.

Arthington, A.H., Bunn, S.E., Poff, N.L., Naiman, R.J., 2006. The challenge of providing environmental flow rules to sustain river ecosystems. Ecological Applications 16 (4), 1311–1318. DOI: 10.1890/1051-0761(2006)016[1311:TCOPEF]2.0.CO;2.

Ban, S.S., Pressey, R.L., Graham, N.A., 2014. Assessing interactions of multiple stressors when data are limited: A Bayesian belief network applied to coral reefs. Global Environmental Change 27, 64–72. DOI: 10.1016/j.gloenvcha.2014.04.018.

Baran, E., Jantunen, T., Chheng, P., 2006. Developing a Consultative Bayesian Model for Integrated Management of Aquatic Resources: an Inland Coastal Zone Case Study, in: Hoan, C.T., Tuong, T.P., Gowing, J.W., Hardy, B. (Eds.), Environment and Livelihoods in Tropical Coastal Zones. Managing Agriculture–Fishery–Aquaculture Conflicts. CAB International, Wallingford, UK, 206–218.

Bashari, H., Smith, C., Bosch, O., 2009. Developing decision support tools for rangeland management by combining state and transition models and Bayesian belief networks. Agricultural Systems 99 (1), 23–34. DOI: 10.1016/j.agsy.2008.09.003.

Bayes, T., Price, R., 1763. An Essay towards Solving a Problem in the Doctrine of Chances. By the Late Rev. Mr. Bayes, F. R. S. Communicated by Mr. Price, in a Letter to John Canton, A. M. F. R. S. Philosophical Transactions of the Royal Society of London 53, 370–418. DOI: 10.1098/rstl.1763.0053.

Baynes, J., Herbohn, J., Russell, I., Smith, C., 2011. Bringing Agroforestry Technology to Farmers in the Philippines: Identifying Constraints to the Success of Extension Activities Using Systems Modelling. Small-scale Forestry 10 (3), 357–376. DOI: 10.1007/s11842-010-9153-8.

BBC News, 2011a. Xinjiang police attack was terrorism, China says. 19 July 2011. http://www.bbc.co.uk/news/world-asia-pacific-14196732. Accessed 26 October 2014.

BBC News, 2011b. China: Unrest in Kashgar, Xinjiang, leaves 15 dead. 31 July 2011. http://www.bbc.co.uk/news/world-asia-pacific-14356532. Accessed 26 October 2014.

BBC News, 2011c. China blames deadly Xinjiang attack on separatists. 1 August 2011. http://www.bbc.co.uk/news/world-asia-pacific-14362544. Accessed 26 October 2014.

BBC News, 2011d. China police kill two suspects in Xinjiang violence. 2 August 2011. http://www.bbc.co.uk/news/world-asia-pacific-14368359. Accessed 26 October 2014.

BBC News, 2011e. Seven 'kidnappers' killed in China's Xinjiang. 29 December 2011. http://www.bbc.co.uk/news/world-asia-china-16351368. Accessed 26 October 2014.

BBC News, 2012a. China violence: 12 dead in Kashgar city in Xinjiang. 29 February 2012. http://www.bbc.co.uk/news/world-asia-china-17195886. Accessed 26 October 2014.

BBC News, 2012b. China violence: '20 dead' in Kashgar city in Xinjiang. 29 February 2012. http://www.bbc.co.uk/news/world-asia-17211909. Accessed 26 October 2014.

BBC News, 2012c. Blast at Xinjiang school injures 17, say China media. 7 June 2012. http://www.bbc.com/news/world-asia-china-18349613. Accessed 26 October 2014.

BBC News, 2013a. Knife attack in China's Xinjiang province kills four. 8 March 2013. http://www.bbc.com/news/world-asia-china-21696265. Accessed 26 October 2014.

BBC News, 2013b. China's Xinjiang hit by deadly clashes. 24 April 2013. http://www.bbc.com/news/world-asia-22276042. Accessed 26 October 2014.

BBC News, 2013c. Violence in China's Xinjiang 'kills 27'. 26 June 2013. http://www.bbc.com/news/world-asia-china-23050288. Accessed 26 October 2014.

BBC News, 2013d. China Xinjiang riots toll 'rises to 35'. 28 June 2013. http://www.bbc.com/news/world-asia-china-23093714. Accessed 26 October 2014.

BBC News, 2013e. China police station attack leaves 11 dead. 17 November 2013. http://www.bbc.com/news/world-asia-china-24976925. Accessed 26 October 2014.

BBC News, 2013f. Sixteen dead in clash in China's Xinjiang. 16 December 2013. http://www.bbc.com/news/world-asia-china-25396448. Accessed 26 October 2014.

BBC News, 2013g. China police kill eight in Xinjiang clash. 30 December 2013. http://www.bbc.com/news/world-asia-china-25546531. Accessed 26 October 2014.

BBC News, 2014a. China: Twelve dead in Xinjiang violence. 27 January 2014. http://www.bbc.com/news/world-asia-china-25858916. Accessed 26 October 2014.

BBC News, 2014b. China kills Xinjiang 'attackers' in Wushi. 14 February 2014. http://www.bbc.com/news/world-asia-china-26192811. Accessed 26 October 2014.

BBC News, 2014c. China: Two dead in Xinjiang violence. 19 March 2014. http://www.bbc.com/news/world-asia-china-26641546. Accessed 26 October 2014.

BBC News, 2014d. Deadly China blast at Xinjiang railway station. 30 April 2014. http://www.bbc.com/news/world-asia-china-27225308. Accessed 26 October 2014.

BBC News, 2014e. Urumqi attack kills 31 in China's Xinjiang region. 23 May 2014. http://www.bbc.com/news/world-asia-china-27502652.

BBC News, 2014f. China police arrest Xinjiang 'terror gang'. 27 May 2014. http://www.bbc.com/news/world-asia-china-27583781. Accessed 26 October 2014.

BBC News, 2014g. China Xinjiang: Police kill 13 attackers. 21 June 2014. http://www.bbc.com/news/world-asia-china-27953164. Accessed 26 October 2014.

Beesley, L., Price, A., King, A.J., Gawne, B., Nielsen, D.L., Koehn, J.D., Meredith, S., Vilizzi, L., Hladyz, S., 2011. Watering floodplain wetlands in the Murray-Darling Basin for native fish. National Water Commission, Canberra, A.C.T.

Borsuk, M., Clemen, R., Maguire, L., Reckhow, K., 2001. Stakeholder Values and Scientific Modeling in the Neuse River Watershed. Group Decision and Negotiation 10 (4), 355–373. DOI: 10.1023/A:1011231801266.

Borsuk, M.E., Stow, C.A., Reckhow, K.H., 2003. Integrated Approach to Total Maximum Daily Load Development for Neuse River Estuary using Bayesian Probability Network Model (Neu-BERN). Journal of Water Resources Planning and Management 129 (4), 271–282. DOI: 10.1061/(ASCE)0733-9496(2003)129:4(271).

Borsuk, M.E., Stow, C.A., Reckhow, K.H., 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecological Modelling 173 (2-3), 219–239. DOI: 10.1016/j.ecolmodel.2003.08.020.

Brisbane Declaration, 2007. http://www.eflownet.org/download_documents/brisbane-declaration-english.pdf. Accessed 23 September 2014.

Bromley, J., 2005. Guidelines for the use of Bayesian networks as a participatory tool for Water Resource Management. Centre for Ecology and Hydrology, Oxon. http://nora.nerc.ac.uk/3300/1/MERITGuidelinesplusApp.pdf. Accessed 23 September 2014.

Burgman, M.A., 2005. Risks and decisions for conservation and environmental management. Cambridge University Press, Cambridge.

Burgman, M.A., McBride, M., Ashton, R., Speirs-Bridge, A., Flander, L., Wintle, B., Fidler, F., Rumpff, L., Twardy, C., 2011. Expert status and performance. PloS ONE 6 (7), e22998. DOI: 10.1371/journal.pone.0022998.

Butcher, R., Hale, J., Muller, K., Kobryn, H., 2009. Ecological character description for the Banrock Station Wetland Complex: Prepared for Department for the Environment, Water, Heritage and the Arts. http://www.environment.gov.au/system/files/resources/39005bbc-6305-4b31-ae15-e7fc25b75325/files/63-ecd.pdf. Accessed 19 September 2014.

Butcher, R., Hale, J., 2011. Ecological Character Description for Hattah-Kulkyne Lakes Ramsar site: Report to the Department of Sustainability, Environment, Water, Population and Communities, Canberra (DSEWPaC). http://www.environment.gov.au/system/files/resources/3bc7df94-e849-459a-b38b-f59edd00fee7/files/16-ecd.pdf. Accessed 19 September 2014.

Cain, J., 2001. Planning improvements in natural resource management: Guidelines for using Bayesian networks to support the planning and management of development programmes in the water sector and beyond. Centre for Ecology and Hydrology, Oxon.

Cain, J., Jinapala, K., Makin, I., Somaratna, P., Ariyaratna, B., Perera, L., 2003. Participatory decision support for agricultural management. A case study from Sri Lanka. Agricultural Systems 76 (2), 457–482. DOI: 10.1016/S0308-521X(02)00006-9.

Carmona, G., Molina, J.L., Bromley, J., Varela-Ortega, C., García-Aróstegui, J.L., 2011a. Object-Oriented Bayesian Networks for Participatory Water Management: Two Case Studies in Spain. Journal of Water Resources Planning and Management 137 (4), 366–376. DOI: 10.1061/(ASCE)WR.1943-5452.0000116.

Carmona, G., Varela-Ortega, C., Bromley, J., 2011b. The Use of Participatory Object-Oriented Bayesian Networks and Agro-Economic Models for Groundwater Management in Spain. Water Resources Management 25 (5), 1509–1524. DOI: 10.1007/s11269-010-9757-y.

Carmona, G., Varela-Ortega, C., Bromley, J., 2013. Participatory modelling to support decision making in water management under uncertainty: two comparative case studies in the Guadiana river basin, Spain. Journal of Environmental Management 128, 400–412. DOI: 10.1016/j.jenvman.2013.05.019.

Castelletti, A., Soncini-Sessa, R., 2007a. Bayesian Networks and participatory modelling in water resource management. Environmental Modelling & Software 22 (8), 1075–1088. DOI: 10.1016/j.envsoft.2006.06.003.

Castelletti, A., Soncini-Sessa, R., 2007b. Coupling real-time control and socio-economic issues in participatory river basin planning. Environmental Modelling & Software 22 (8), 1114–1128. DOI: 10.1016/j.envsoft.2006.05.018.

Catenacci, M., Giupponi, C., 2013. Integrated assessment of sea-level rise adaptation strategies using a Bayesian decision network approach. Environmental Modelling & Software 44, 87–100. DOI: 10.1016/j.envsoft.2012.10.010.

Chan, T., Ross, H., Hoverman, S., Powell, B., 2010. Participatory development of a Bayesian network model for catchment-based water resource management. Water Resources Research 46 (7), W07544. DOI: 10.1029/2009WR008848.

Chan, T.U., Hart, B.T., Kennard, M.J., Pusey, B.J., Shenton, W., Douglas, M.M., Valentine, E., Patel, S., 2012. Bayesian network models for environmental flow decision making in the Daly River, Northern Territory, Australia. River Research and Applications 28 (3), 283–301. DOI: 10.1002/rra.1456.

Charniak, E., 1991. Bayesian Networks without tears. AI Magazine 12 (4), 50–63.

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environmental Modelling & Software 37, 134–145. DOI: 10.1016/j.envsoft.2012.03.012.

China Digital Times, 2011. China Sends Anti-terrorism Unit to Restive West. 13 August 2011. http://chinadigitaltimes.net/2011/08/china-sends-anti-terrorism-unit-to-restive-west/. Accessed 28 October 2014.

Clemen, R.T., Winkler, R.L., 1999. Combining Probability Distributions From Experts in Risk Analysis. Risk Analysis 19 (2), 187–203.

Coupé, V.M., van der Gaag, L.C., 2002. Properties of sensitivity analysis of Bayesian belief networks. Annals of Mathematics and Artificial Intelligence 36 (4), 323–356. DOI: 10.1023/A:1016398407857.

CSIRO, 2012. Assessment of the ecological and economic benefits of environmental water in the Murray-Darling Basin. CSIRO Water for a Healthy Country National Research Flagship, Australia. http://www.mdba.gov.au/kid/files/2017-Assessment_Ecological_Economic_Benefits.pdf. Accessed 12 September 2014.

Das, B., 2004. Generating Conditional Probabilities for Bayesian Networks: Easing the Knowledge Acquisition Problem. Computing Research Repository cs.AI/0411034.

Department of Environment and Climate Change NSW, 2008. Ecological character description: Blue Lake Ramsar site, Sydney. http://www.environment.nsw.gov.au/resources/water/08273bluelakeecd.pdf. Accessed 19 September 2014.

Department of Sustainability and Environment VIC, 2010. Kerang Wetlands Ramsar Site: Ecological character description.

Donald, M., Cook, A., Mengersen, K., 2009. Bayesian network for risk of diarrhea associated with the use of recycled water. Risk Analysis 29 (12), 1672–1685. DOI: 10.1111/j.1539-6924.2009.01301.x.

Draxler, R.R., Gillette, D.A., Kirkpatrick, J.S., Heller, J., 2001. Estimating PM10 air concentrations from dust storms in Iraq, Kuwait and Saudi Arabia. Atmospheric Environment 35 (25), 4315–4330. DOI: 10.1016/S1352-2310(01)00159-5.

Drew, C.A., Collazo, J.A., 2012. Expert Knowledge as a Foundation for the Management of Secretive Species and Their Habitat, in: Perera, A.H., Drew, C.A., Johnson, C.J. (Eds.), Expert knowledge and its application in landscape ecology. Springer, New York, NY, 87–107.

Drew, C.A., Perera, A.H., 2012. Expert Knowledge as a Basis for Landscape Ecological Predictive Models, in: Perera, A.H., Drew, C.A., Johnson, C.J. (Eds.), Expert knowledge and its application in landscape ecology. Springer, New York, NY, 229–248.

Druzdzel, M.J., 1996. Qualitative Verbal Explanations in Bayesian Belief Networks. Artificial Intelligence and Simulation of Behaviour Quarterly 94, 43–54.

Düspohl, M., Frank, S., Döll, P., 2012. A Review of Bayesian Networks as a Participatory Modeling Approach in Support of Sustainable Environmental Management. Journal of Sustainable Development 5 (12), 1–18. DOI: 10.5539/jsd.v5n12p1.

Epstein, Y., Moran, D.S., 2006. Thermal Comfort and the Heat Stress Indices. Industrial Health 44, 388–398.

Fang, J., 2008. Chongxin renshi shachenbao. Minfang fan (Civil Defense Realm) 2, 12–13.

Fenton, N., Neil, M., 2007. Managing risk in the modern world: Applications of Bayesian Networks. A Knowledge Transfer Report from the London Mathematical Society and the Knowledge Transfer Network for Industrial Mathematics. London Mathematical Society, London.

Fisk, G., 2009. Ecological Character Description of Currawinya Lakes Ramsar Site: Prepared for Queensland Environmental Protection Agency.

Florin, M.J., van Ittersum, Martin K., van de Ven, Gerrie W.J., 2013. Family farmers and biodiesel production: Systems thinking and multi-level decisions in Northern Minas Gerais, Brazil. Agricultural Systems 121, 81–95. DOI: 10.1016/j.agsy.2013.07.002.

Frank, S.K., Döll, P., Welp, M., Halik, Ü., Yimit, H., 2014a. Assessing environmental trade-offs with Bayesian Decision Networks: Comparing ecosystem services and irrigation needs of urban and peri-urban plant species in Xinjiang, NW China, in: Proceedings of the 7th International Congress on Environmental Modelling and Software, San Diego, California, USA. June 15-19, 2014. http://www.iemss.org/sites/iemss2014/proceedings.php. Accessed 12 September 2014.

Frank, S.K., Pollino, C.A., Döll, P., 2014b. Using Bayesian Networks to link Environmental Flows to Ecosystem Services in the Murray-Darling Basin, Australia, in: Proceedings of the 7th International Congress on Environmental Modelling and Software, San Diego, California, USA. June 15-19, 2014. http://www.iemss.org/sites/iemss2014/proceedings.php. Accessed 12 September 2014.

Freeman, R.E., 1984. Strategic management: A stakeholder approach. University Press, Cambridge.

Gao, J., Jing, L.-h., 2009. Tacheng diqu shachen tianqi bianhua tezheng (Analysis on the Variation Characteristics of Dust Weather in Tacheng Region). Qihou bianhua yanjiu jinzhan (Advances in Climate Change Research) 5 (5), 271–277.

Georgi, J.N., Dimitriou, D., 2010. The contribution of urban green spaces to the improvement of environment in cities: Case study of Chania, Greece. Building and Environment 45 (6), 1401–1414. DOI: 10.1016/j.buildenv.2009.12.003.

Goudie, A.S., Middleton, N.J., 2006. Desert dust in the global system. Springer, Berlin, Heidelberg, New York.

Grêt-Regamey, A., Brunner, S.H., Altwegg, J., Christen, M., Bebi, P., 2013. Integrating Expert Knowledge into Mapping Ecosystem Services Trade-offs for Sustainable Forest Management. Ecology and Society 18 (3). DOI: 10.5751/ES-05800-180334.

Grimble, R., Wellard, K., 1997. Stakeholder methodologies in natural resource management: a review of principles, contexts, experiences and opportunities. Agricultural Systems 55 (2), 173–193. DOI: 10.1016/S0308-521X(97)00006-1.

Grimble, R., 1998. Stakeholder methodologies in natural resource management: Socioeconomic Methodologies. Best Practice Guidelines. Natural Resources Institute, Chatham, UK.

Haapasaari, P., Karjalainen, T.P., 2010. Formalizing expert knowledge to compare alternative management plans: Sociological perspective to the future management of Baltic salmon stocks. Marine Policy 34 (3), 477–486. DOI: 10.1016/j.marpol.2009.10.002.

Haapasaari, P., Mäntyniemi, S., Kuikka, S., 2013. Involving stakeholders in building integrated fisheries models using Bayesian methods. Environmental Management 51 (6), 1247–1261. DOI: 10.1007/s00267-013-0041-9.

Hale, J., Butcher, R., 2011. Ecological Character Description for the Barmah Forest Ramsar Site: Report to the Department of Sustainability, Environment, Water, Population and Communities, Canberra (DSEWPaC). http://www.environment.gov.au/system/files/resources/e0276868-d587-4ce6-810b-e1d558acbd4e/files/14-ecd.pdf. Accessed 19 September 2014.

Halik, Ü., 2003. Stadtbegrünung im ariden Milieu: Das Beispiel der Oasenstädte des südlichen Xinjiang/VR China; unter besonderer Berücksichtigung ökologischer, sozioökonomischer und kulturhistorischer Aspekte. TU, Univ.-Bibliothek, Abt. Publ., Berlin.

Hamilton, G.S., Fielding, F., Chiffings, A.W., Hart, B.T., Johnstone, R.W., Mengersen, K., 2007. Investigating the Use of a Bayesian Network to Model the Risk of Lyngbya majuscula Bloom Initiation in Deception Bay, Queensland, Australia. Human and Ecological Risk Assessment 13 (6), 1271–1287. DOI: 10.1080/10807030701655616.

Hansson, F., Sjökvist, S., 2013. Modelling expert judgement into a Bayesian Belief Network: A method for consistent and robust determination of conditional probability tables. Master's thesis. Lund University, Lund, Sweden. 2013. http://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=3866733&fileOId=3866740. Accessed 12 September 2014.

He, Q., Yang, X., Mamtimin, A., Tang, S., 2011. Impact factors of soil wind erosion in the center of Taklimakan Desert. Journal of Arid Land 3 (1), 9–14. DOI: 10.3724/SP.J.1227.2011.00009.

Henriksen, H.J., Rasmussen, P., Brandt, G., Bülow, D. von, Jensen, F.V., 2007. Public participation modelling using Bayesian networks in management of groundwater contamination. Environmental Modelling & Software 22 (8), 1101–1113. DOI: 10.1016/j.envsoft.2006.01.008.

Holzkämper, A., Kumar, V., Surridge, Ben W J, Paetzold, A., Lerner, D.N., 2012. Bringing diverse knowledge sources together - a meta-model for supporting integrated catchment management. Journal of Environmental Management 96 (1), 116–127. DOI: 10.1016/j.jenvman.2011.10.016.

Hu, X., Li, K., 2011. Cong chengshi guihua jiaodu tantao ruhe jianshe ziyuan jieyuexing shehui. Zhongxiao qiye guanli yu keji 2, 98.

Huo, Y., 2009. Jiankang „shashou“ shachenbao. Shengming yu zaihai (Life and Disaster) 4, 31–32.

Iqbal, J., MacLean, D.A., 2010. Prediction of balsam fir sawfly defoliation using a Bayesian network model. Canadian Journal of Forest Research 40 (12), 2322–2332. DOI: 10.1139/X10-174.

Jensen, F.V., Nielsen, T.D., 2007. Bayesian networks and decision graphs, 2nd ed. Springer, New York.

Jensen, T.B., Kristensen, A.R., Toft, N., Baadsgaard, N.P., Østergaard, S., Houe, H., 2009. An object-oriented Bayesian network modeling the causes of leg disorders in finisher herds. Preventive Veterinary Medicine 89 (3-4), 237–248. DOI: 10.1016/j.prevetmed.2009.02.009.

Jin, J. (Ed.), 2010. Xin jiang tong ji nian jia: Xinjiang Statistical Yearbook, 1st ed. Zhong guo tong ji chu ban she, Beijing.

Johnson, S., Mengersen, K., Waal, A. de, Marnewick, K., Cilliers, D., Houser, A.M., Boast, L., 2010. Modelling cheetah relocation success in southern Africa using an Iterative Bayesian Network Development Cycle. Ecological Modelling 221 (4), 641–651. DOI: 10.1016/j.ecolmodel.2009.11.012.

Kang, W., Wu, Y., He, J., Wu, X., 2011. Chengshi redao xiaoying de yanjiu jinzhan (Research Progress of Urban Heat Island effect). Zhongnan linye keji daxue xuebao (Journal of Central South University of Forestry and Technology) 31 (1), 70–76.

Kingsford, R.T., Lee, E., 2010. Ecological character description of the Paroo River Wetlands Ramsar site. http://www.environment.nsw.gov.au/resources/water/10213parooriverecd.pdf. Accessed 19 September 2014.

Kjaerulff, U.B., Madsen, A.L., 2008. Bayesian networks and influence diagrams: A guide to construction and analysis. Springer, New York.

Klimacampus, 2011. Zwischen Betonwüste und Baumoase. Die Städte der Zukunft, in: Exzellenzcluster CliSAP (Ed.), Klima im Fokus, 22–27.

Korb, K.B., Nicholson, A.E., 2011. Bayesian artificial intelligence, 2nd ed. CRC Press, Boca Raton, FL.

Koski, T., Noble, J.M., 2009. Bayesian networks: An introduction. Wiley, Chichester, West Sussex, UK.

Krueger, T., Page, T., Hubacek, K., Smith, L., Hiscock, K., 2012. The role of expert opinion in environmental modelling. Environmental Modelling & Software 36, 4–18. DOI: 10.1016/j.envsoft.2012.01.011.

Kumar, V., Rouquette, J.R., Lerner, D.N., 2012. Integrated modelling for Sustainability Appraisal for Urban River Corridor (re)-development. Procedia Environmental Sciences 13, 687–697. DOI: 10.1016/j.proenv.2012.01.062.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environmental Modelling & Software 46, 1–11. DOI: 10.1016/j.envsoft.2013.03.011.

Laniak, G.F., Olchin, G., Goodall, J., Voinov, A., Hill, M., Glynn, P., Whelan, G., Geller, G., Quinn, N., Blind, M., Peckham, S., Reaney, S., Gaber, N., Kennedy, R., Hughes, A., 2013. Integrated environmental modeling: A vision and roadmap for the future. Environmental Modelling & Software 39, 3–23. DOI: 10.1016/j.envsoft.2012.09.006.

Liu, K.F.-R., Chen, C.-W., Shen, Y.-S., 2013. Using Bayesian belief networks to support health risk assessment for sewer workers. International Journal of Environmental Science and Technology 10 (2), 385–394. DOI: 10.1007/s13762-012-0136-5.

Low-Choy, S., James, A., Murray, J., Mengersen, K., 2012. Elicitator: A User-Friendly, Interactive Tool to Support Scenario-Based Elicitation of Expert Knowledge, in: Perera, A.H., Drew, C.A., Johnson, C.J. (Eds.), Expert knowledge and its application in landscape ecology. Springer, New York, NY, 39–68.

Luo, J., Zheng, X., Zhu, F., Di Xian, Yang, W., Tu, Z., Li, M., 2011. Zhongguo shachenbao fasheng de qixiang weixiandu yanjiu (Meteorologically Dangerous Level of Dust Storm Occurrence in China). Zhongguo shamo (Journal of Desert Research) 31 (1), 185–190.

Lynam, T., Jong, W. de, Sheil, D., Kusumanto, T., Evans, K., 2007. A Review of Tools for Incorporating Community Knowledge, Preferences, and Values into Decision Making in Natural Resources Management. Ecology and Society 12 (1).

Marcot, B.G., Steventon, J.D., Sutherland, G.D., McCann, R.K., 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Canadian Journal of Forest Research 36 (12), 3063–3074. DOI: 10.1139/X06-135.

Martin, T.G., Kuhnert, P.M., Mengersen, K., Possingham, H.P., 2005. The Power of Expert Opinion in Ecological Models using Bayesian Methods: Impact of Grazing on Birds. Ecological Applications 15 (1), 266–280. DOI: 10.1890/03-5400.

Martínez-Arroyo, A., Jáuregui, E., 2000. On the environmental role of urban lakes in Mexico City. Urban Ecosystems 4, 145–166.

McCann, R.K., Marcot, B.G., Ellis, R., 2006. Bayesian belief networks: applications in ecology and natural resource management. Canadian Journal of Forest Research 36 (12), 3053–3062. DOI: 10.1139/X06-238.

McCloskey, J.T., Lilieholm, R.J., Cronan, C., 2011. Using Bayesian belief networks to identify potential compatibilities and conflicts between development and landscape conservation. Landscape and Urban Planning 101 (2), 190–203. DOI: 10.1016/j.landurbplan.2011.02.011.

McDowell, R.W., Nash, D., George, A., Wang, Q.J., Duncan, R., 2009. Approaches for quantifying and managing diffuse phosphorus exports at the farm/small catchment scale. Journal of Environmental Quality 38 (5), 1968–1980. DOI: 10.2134/jeq2007.0651.

Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.

Minsky, M., 1961. Steps toward Artificial Intelligence. Proceedings of the IRE 49 (1), 8–30. DOI: 10.1109/JRPROC.1961.287775.

Moglia, M., Perez, P., Burn, S., 2012. Assessing the likelihood of realizing idealized goals: The case of urban water strategies. Environmental Modelling & Software 35, 50–60. DOI: 10.1016/j.envsoft.2012.02.005.

Money, E.S., Reckhow, K.H., Wiesner, M.R., 2012. The use of Bayesian networks for nanoparticle risk forecasting: Model formulation and baseline evaluation. Science of the Total Environment 426, 436–445. DOI: 10.1016/j.scitotenv.2012.03.064.

Montewka, J., Weckström, M., Kujala, P., 2013. A probabilistic model estimating oil spill clean-up costs - a case study for the Gulf of Finland. Marine Pollution Bulletin 76 (1-2), 61–71. DOI: 10.1016/j.marpolbul.2013.09.031.

Morgan, M.G., Henrion, M., 1990. Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, Cambridge, New York.

Murray, J.V., Stokes, K.E., Klinken, R.D., 2012. Predicting the potential distribution of a riparian invasive plant: the effects of changing climate, flood regimes and land-use patterns. Global Change Biology 18 (5), 1738–1753. DOI: 10.1111/j.1365-2486.2011.02621.x.

Murray-Darling Basin Authority, n.d. Murray-Darling Ramsar wetlands spatial data.

Murray-Darling Basin Authority, 2011. The proposed "environmentally sustainable level of take" for surface water of the Murray-Darling Basin: Methods and outcomes. MDBA publication 226/11, Canberra. http://www.mdba.gov.au/sites/default/files/archived/proposed/ESLT_MDBA_report.pdf. Accessed 12 September 2014.

Nash, D., Hannah, M., Robertson, F., Rifkin, P., 2010. A Bayesian Network for Comparing Dissolved Nitrogen Exports from High Rainfall Cropping in Southeastern Australia. Journal of Environment Quality 39 (5), 1699–1710. DOI: 10.2134/jeq2009.0348.

Newall, P.R., Lloyd, L.N., Gell, P.A., Walker, K.F., 2008. Ecological Character Description for the Riverland Ramsar Site – Draft v1-8.: Lloyd Environmental Pty Ltd Report (Project No: LE0739) to Department for Environment and Heritage SA.

Newton, A.C., Stewart, G.B., Diaz, A., Golicher, D., Pullin, A.S., 2007. Bayesian Belief Networks as a tool for evidence-based conservation management. Journal for Nature Conservation 15 (2), 144–160. DOI: 10.1016/j.jnc.2007.03.001.

Nolivos, I., van Biesen, L., Swennen, R.L., 2011. Modelling an Intensive Banana Cropping System in Ecuador Using a Bayesian Network, in: Proceedings of the XXVIIIth International Horticultural Congress on Science and Horticulture for

People. International Symposium on Engineering the Modelling, Monitoring, Mechanization and Automation Tools for Precision Horticulture, Lisbon, Portugal. International Society for Horticultural Science, Leuven, Belgium, 89–98.

Norsys Software Corp., 2010. Netica-J Manual: Version 4.18 and Higher. http://www.norsys.com/netica-j/docs/NeticaJ_Man.pdf. Accessed 16 September 2014.

Norsys Software Corp., n.d. Netica's Help System. https://www.norsys.com/WebHelp/NETICA.htm. Accessed 12 September 2014.

Office of Environment and Heritage NSW, 2012. Macquarie Marshes Ramsar site: Ecological character description. Macquarie Marshes Nature Reserve and U-block components. http://www.environment.nsw.gov.au/resources/water/120517MMECDPt1.pdf. Accessed 19 September 2014.

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

Pahl-Wostl, C., Arthington, A., Bogardi, J., Bunn, S.E., Hoff, H., Lebel, L., Nikitina, E., Palmer, M., Poff, L.N., Richards, K., Schlüter, M., Schulze, R., St-Hilaire, A., Tharme, R., Tockner, K., Tsegai, D., 2013. Environmental flows and water governance: managing sustainable water uses. Current Opinion in Environmental Sustainability 5 (3-4), 341–351. DOI: 10.1016/j.cosust.2013.06.009.

Pan, X., 2010. Shachenbao jiankang xiaoying de yanjiu jinzhan yu zhanwang. Huanjing yu jiankang zazhi (Journal of Environment and Health) 27 (9), 753–754.

Paproth, 2004. Map of the Tarim Basin: Modified by Pietsch 2011. Institute of Applied Physical Geography of the Catholic University of Eichstätt-Ingolstadt.

Pearl, J., 1982. Reverend Bayes on inference engines: A distributed hierarchical approach, in: Proceedings of the Second National Conference on Artificial Intelligence. The AAAI Press, 133–136. http://psych.stanford.edu/~jlm/pdfs/PearlAAAI82-032.pdf. Accessed 2 October 2014.

Pearlmutter, D., Berliner, P., Shaviv, E., 2007. Urban climatology in arid regions: current research in the Negev desert. International Journal of Climatology 27 (14), 1875–1885. DOI: 10.1002/joc.1523.

Pellikka, J., Kuikka, S., Lindén, H., Varis, O., 2005. The role of game management in wildlife populations: uncertainty analysis of expert knowledge. European Journal of Wildlife Research 51 (1), 48–59. DOI: 10.1007/s10344-004-0073-9.

Penman, T.D., Price, O., Bradstock, R.A., 2011. Bayes Nets as a method for analysing the influence of management actions in fire planning. International Journal of Wildland Fire 20 (8), 909–920. DOI: 10.1071/WF10076.

Pike, W.A., 2004. Modeling drinking water quality violations with Bayesian Networks. Journal of the American Water Resources Association 40 (6), 1563–1578. DOI: 10.1111/j.1752-1688.2004.tb01606.x.

Poff, N.L., Zimmerman, J.K.H., 2010. Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. Freshwater Biology 55 (1), 194–205. DOI: 10.1111/j.1365-2427.2009.02272.x.

Pollack, H.N., 2003. Uncertain science… Uncertain world. Cambridge University Press, Cambridge, New York.

Pollino, C.A., Henderson, C., 2010. Bayesian networks: A guide for their application in natural resource management and policy. Technical Report No 14. http://150.203.60.53/site/system/files/35/original/No_14_BNs_a_resource_guide.pdf?1275920191. Accessed 12 September 2014.

Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environmental Modelling & Software 22 (8), 1140–1152. DOI: 10.1016/j.envsoft.2006.03.006.

Qi, K., 2009. Guihuake (shi): Chengshi fangzai (Planning Class X: Urban Disaster Prevention). Xiandai chengshi yanjiu (Modern Urban Research) 10, 29–31.

Ramsar, 2005. COP9 Resolution IX.1 Annex A. http://www.ramsar.org/pdf/res/key_res_ix_01_annexa_e.pdf. Accessed 12 September 2014.

Ren, J., Jenkinson, I., Wang, J., Xu, D.L., Yang, J.B., 2008. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. Journal of Safety Research 39 (1), 87–100. DOI: 10.1016/j.jsr.2007.09.009.

Renooij, S., Witteman, C., 1999. Talking probabilities: communicating probabilistic information with words and numbers. International Journal of Approximate Reasoning 22 (3), 169–194. DOI: 10.1016/S0888-613X(99)00027-4.

Richards, R., Sanó, M., Roiko, A., Carter, R.W., Bussey, M., Matthews, J., Smith, T.F., 2013. Bayesian belief modeling of climate change impacts for informing regional adaptation options. Environmental Modelling & Software 44, 113–121. DOI: 10.1016/j.envsoft.2012.07.008.

Russi, D., Brink, P. ten, Farmer, A., Badura, T., Coates, D., Förster, J., Kumar, R., Davidson, N., 2013. The Economics of Ecosystems and Biodiversity (TEEB) for Water and Wetlands. IEEP, London and Brussels; Ramsar Convention Secretariat, Gland. http://doc.teebweb.org/wp-content/uploads/2013/04/TEEB_WaterWetlands_Report_2013.pdf. Accessed 20 October 2014.

Schmitt, L.H.M., Brugere, C., 2013. Capturing ecosystem services, stakeholders' preferences and trade-offs in coastal aquaculture decisions: A Bayesian belief network application. PloS ONE 8 (10), e75956. DOI: 10.1371/journal.pone.0075956.

Seidel, M., Breslin, C., Christley, R., Gettinby, G., Reid, S., Revie, C., 2003. Comparing diagnoses from expert systems and human experts. Agricultural Systems 76 (2), 527–538. DOI: 10.1016/S0308-521X(02)00035-5.

Shenton, W., Hart, B.T., Chan, T., 2011. Bayesian network models for environmental flow decision-making: 1. Latrobe River Australia. River Research and Applications 27 (3), 283–296. DOI: 10.1002/rra.1348.

Shenton, W., Hart, B.T., Chan, T.U., 2014. A Bayesian network approach to support environmental flow restoration decisions in the Yarra River, Australia. Stochastic Environmental Research and Risk Assessment 28 (1), 57–65. DOI: 10.1007/s00477-013-0698-x.

Shi, P., Yan, P., Gao, S., Wang, Y., Ha, S., Yu, Y., 2000. Wo guo shachenbao zaihai ji qi yanjiu jinzhan yu zhanwang (The duststorm disaster in China and its research progress). Ziran zaihai xuebao (Journal of Natural Disasters) 9 (3), 71–77.

Siew, T.-F., Döll, P., 2012. Transdisciplinary research for supporting the inte-gration of ecosystem services into land and water management in the Tarim River Basin, Xinjiang, China. Journal of Arid Land 4 (2), 196–210. DOI: 10.3724/SP.J.1227.2012.00196.

Smith, C., van Klinken, Rieks D., Seabrook, L., McAlpine, C., 2012. Estimating the influence of land management change on weed invasion potential using expert knowledge. Diversity and Distributions 18 (8), 818–831. DOI: 10.1111/j.1472-4642.2011.00871.x.

Smith, C.S., Howes, A.L., Price, B., McAlpine, C.A., 2007. Using a Bayesian belief network to predict suitable habitat of an endangered mammal – The Julia Creek dunnart (Sminthopsis douglasi). Biological Conservation 139 (3-4), 333–347. DOI: 10.1016/j.biocon.2007.06.025.

Tao, J.-h., 2009. Xibei diqu shachen tianqi de shikong tezheng ji yingxiang yinsu fenxi (Spatial-temporal Characteristics of Sand-dust Events and Influencing Factors in Northwest China). Zhongguo shamo (Journal of Desert Research) 29 (2), 327–334.

Thom, E.C., 1959. The distribution index. Weatherwise 12 (2), 57–60.

Ticehurst, J., Curtis, A., Merritt, W., 2011. Using Bayesian Networks to complement conventional analyses to explore landholder management of native vegetation. Environmental Modelling & Software 26 (1), 52–65. DOI: 10.1016/j.envsoft.2010.03.032.

Tiller, R., Gentry, R., Richards, R., 2013. Stakeholder driven future scenarios as an element of interdisciplinary management tools; the case of future offshore aquaculture development and the potential effects on fishermen in Santa Barbara, California. Ocean & Coastal Management 73, 127–135. DOI: 10.1016/j.ocecoaman.2012.12.011.

Troldborg, M., Aalders, I., Towers, W., Hallett, P.D., McKenzie, B.M., Bengough, A.G., Lilly, A., Ball, B.C., Hough, R.L., 2013. Application of Bayesian Belief Networks to quantify and map areas at risk to soil threats: Using soil compaction as an example. Soil and Tillage Research 132, 56–68. DOI: 10.1016/j.still.2013.05.005.

TuTiempo, 2014. Daily average temperature and humidity data Korla (meteorological station 516560): July 2012. http://www.tutiempo.net/clima/KORLA/07-2012/516560.htm.

Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. Science 185 (4157), 1124–1131.

Uusitalo, L., Kuikka, S., Romakkaniemi, A., 2005. Estimation of Atlantic salmon smolt carrying capacity of rivers using expert knowledge. ICES Journal of Marine Science 62 (4), 708–722. DOI: 10.1016/j.icesjms.2005.02.005.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecological Modelling 203 (3-4), 312–318. DOI: 10.1016/j.ecolmodel.2006.11.033.

van Dam, A.A., Kipkemboi, J., Rahman, M.M., Gettel, G.M., 2013. Linking Hydrology, Ecosystem Function, and Livelihood Outcomes in African Papyrus Wetlands Using a Bayesian Network Model. Wetlands 33 (3), 381–397. DOI: 10.1007/s13157-013-0395-z.

Van Den Hoek, J., Baumgartner, J., Doucet-Beer, E., Hildebrandt, T., Robinson, B.E., Zinda, J.A., 2012. Understanding the Challenges and Rewards of Social-Ecological Research in China. Society & Natural Resources 25 (12), 1324–1329. DOI: 10.1080/08941920.2012.658985.

van der Gaag, L., Renooij, S., Witteman, C., Aleman, B., Taal, B.G., 2002. Probabilities for a probabilistic network: a case study in oesophageal cancer. Artificial Intelligence in Medicine 25 (2), 123–148. DOI: 10.1016/S0933-3657(02)00012-X.

Varis, O., Rahaman, M.M., Kajander, T., 2012. Fully connected Bayesian belief networks: A modeling procedure with a case study of the Ganges river basin. Integrated Environmental Assessment and Management 8 (3), 491–502. DOI: 10.1002/ieam.222.

Vilizzi, L., Price, A., Beesley, L., Gawne, B., King, A.J., Koehn, J.D., Meredith, S.N., Nielsen, D.L., Sharpe, C.P., 2012. The belief index: An empirical measure for evaluating outcomes in Bayesian belief network modelling. Ecological Modelling 228, 123–129. DOI: 10.1016/j.ecolmodel.2012.01.005.

Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environmental Modelling & Software 25 (11), 1268–1281. DOI: 10.1016/j.envsoft.2010.03.007.

Wang, C., Shi, J., 2010. Nanjiang pendi da fan wei qiang shachen tianqi fenxi (Analysis of Dust-devil Weather of the Southern Xinjiang). Kongzhong jiaotong guanli (Air Traffic Management) 2, 45–53.

Wang, Q.J., Robertson, D.E., Haines, C.L., 2009a. A Bayesian network approach to knowledge integration and representation of farm irrigation: 1. Model development. Water Resources Research 45 (2), W02409. DOI: 10.1029/2006WR005419.

Wang, S., Kurban, A., Guo, Y., Duan, H., 2009b. Wulumuqi diqu qiwen bianhua he chengshi redao xiaoying fenxi (Study on Temperature Change and Urban Heat Island Effect in the Urumqi Region). Ganhanqu yanjiu (Arid Zone Research) 26 (3), 433–440.

Wild, A., Roberts, S., Smith, B., Noble, D., Brereton, R., 2010. Ecological Character Description: Ginini Flats Wetland Complex: Report to the Australian Government Department of Sustainability, Environment, Water, Population and Communities. Unpublished report prepared by Entura, Hobart, Canberra. http://www.environment.gov.au/system/files/resources/1ad9f676-2669-4263-96b4-7672a053bfd5/files/45-ecd.pdf. Accessed 19 September 2014.

Williams, B.J., Cole, B., 2013. Mining monitored data for decision-making with a Bayesian network model. Ecological Modelling 249, 26–36. DOI: 10.1016/j.ecolmodel.2012.07.008.

Yabuki, S., Mikami, M., Nakamura, u., Kanayama, S., Fu, F., Liu, M., Zhou, H., 2005. The Characteristics of Atmospheric Aerosol at Aksu, an Asian Dust-Source Region of North-West China: A Summary of Observations over the Three Years from March 2001 to April 2004. Journal of the Meteorological Society of Japan 83A, 45–72.

Yan, L., 2010. Wutuan kenqu qixiang zaihai ji fangyu duice. Xiandai nongye keji (Modern Agricultural Sciences and Technology) 5, 287–288.

Zhou, J., Zhao, X.-g., Wang, Q., Ayisadaiti, A., Jian, H., 2010. Xinjiang nanbu san chengshi shachen tianqi dui xiaoxuesheng shang huxidao ji yan bushi zhengzhuang de yingxiang (Effects of Dust Event on the Upper Respiratory Tract and Eyes Uncomfortable Symptoms of Primary School Students in Southern Xinjiang). Huanjing yu jiankang zazhi (Journal of Environment and Health) 27 (9), 767–771.

Appendices

Appendix A Literature review

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013. (DAG = directed acyclic graph/network structure, CPT = conditional probability table, E = expert, D = empirical data, M = model simulations, L = scientific literature, S = stakeholder)

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Allan et al. (2012); CS 1	BN with 24 nodes	**DAG**	E		Stream ecologists	Group meeting with group discussions (2-day WS)	• Validation of preliminary DAG		
		CPT	E				<u>Other</u> • Quantile elicitation (Allan et al., 2012: 62)		
Amstrup et al. (2008)	BN with 38 nodes (Netica)	**DAG**	E	1	Polar bear expert	Individual meetings	<u>Probability tables</u> • Step-by-step guidance through whole BN modeling process		
		CPT	E						
Baran et al. (2006)	BN with 43 nodes (Netica)	**DAG**	S	10-15	Fishers, farmers, aquaculturists, representatives of local organizations	Group meetings with group discussions (6 half-day consultations in 3 communes)	• Development of DAG from scratch (after task was introduced with example DAG)		
		CPT	D,M,S	10-15			<u>Weights</u> • Elicitation of unconditional probabilities for root nodes • Elicitation of weights for each parent node (Baran et al., 2006: 214ff.)	• Probability values derived from probabilities of parent nodes and weights	• Group consensus; averaging of probability values only in case of disagreement
Bashari et al. (2009)	BN with 21 nodes	**DAG**	E,L,S		WS I: Livestock owners, WS II: Rangeland scientists	Group meeting with group discussions (2 WS)	• Development of a state and transition model (STM)	• Conversion of STM into DAG	
		CPT	E		Rangeland scientists	Unknown	<u>Probability tables</u> • Elicitation of conditional probability values for a reduced number of scenarios (p. 26ff)	• Interpolation of other probability values (Cain 2001)	

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Baynes et al. (2011)	4 BNS with 15, 8, 9, and 13 nodes (Netica)	**CPT**	D,S	7 7	Farmers Non-farmers who employed farm labor	Group meeting with one-to-one sessions (1 WS)	Probability tables • Elicitation of unconditional probability values with Likert scale (incl. comment) • Elicitation of conditional probability values for a reduced number of scenarios • Elicitation of weights for each parent node (Baynes et al., 2011: 362ff.)	• Interpolation of other probability values (Cain 2001)	• Averaging of valid Likert scale responses
Borsuk et al. (2004) (incl. Borsuk et al., 2001)	BN with 8 sub-models (Analytica)	**CPT**	D,E,M	2 2	Marine biologists Estuarine fisheries researchers	Unknown ("series of meetings")	Frequencies • Example: "If you were to observe 100 vertical mixing events, how many do you think would be less than x days apart?" (Borsuk et al., 2001: 365)		
Cain et al. (2003)	6 DAGs (Hugin and Netica)	**DAG**	S	30 9 11	Representatives of gov. organizations (WS 1); Farmers from head of the basin (WS 2); Farmers from tail of the basin (WS 3)	Group meetings with group discussions (WS 1, 6h; WS 2, and WS 3, 4.5h each)	• WS 1: Development of 4 DAGs in 4 groups • WS 2 and 3: Semi-structured discussions to elicit information necessary for facilitators to develop DAGs		
		CPT	S	30	Representatives of gov. organizations (WS 1)		Probability tables • WS 1: One group defined probability values		
Carmona et al. (2013) (CS 1)	OOBN with 32 nodes coupled with other model (Hugin)	**DAG**	E,S	9 + 6	Representatives of the River Basin Authority, regional government organizations, main irrigation communities, environmental NGOs, researchers	Group meetings with group discussions	• Development of two DAGs in two separate sessions with different stakeholder groups		
				12		Individual meetings	• Validation of combined DAG		
		CPT	E,M,S	11		Group meeting	Probability tables		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	**BN facts (BN soft-ware)**	**Knowledge source**		**Number and background of experts/stakeholders**		**Consultation format**	**Elicitation format**	**Derivation of probability values**	**Combination of DAGs and probability values**
Castelletti and Soncini-Sessa (2007b)	BN with 5 nodes coupled with other models (Hugin)	**CPT**	S		Farmers	Individual meetings (interviews)	<u>Probability tables</u> • Some probability values a priori fixed as either null or irrelevant • Elicitation of remaining probability values	• CPTs based on the computed convolution for elicited probability distributions (Castelletti and Soncini-Sessa, 2007b: 1123)	
Catenacci and Giupponi (2013)	BDN with 17 nodes, 24 links (GeNIe)	**DAG**	E	19	Researchers with (multidisciplinary) backgrounds in 24 disciplines	Group meeting	• Development of conceptual maps using Cmap software • Elicitation of rankings of variables which were translated into an “objectives’ hierarchy chart”	• Development of DAG with selected nodes from the “objectives’ hierarchy chart”	
		CPT	E			Individual meetings (interviews)	<u>Probability tables</u> • Elicitation according to expertise		• Averaging of probability values by using linear opinion pooling (Clemen and Winkler, 1999: 189)
Chan et al. (2010)	BN with 49 nodes (Netica)	**CPT**	D,E		“Expert” subset of stakeholders with technical backgrounds	Group meeting with group discussion and individual meetings	<u>Probability tables</u> • Elicitation according to expertise		• Averaging of probability values
Chan et al. (2012)	2 BNs: 24 and 27 nodes	**DAG**	E		Fish experts	Group meeting (WS)	• Development of DAG		
		CPT	E,M		Fish experts	Unknown	<u>Probability tables</u>		
Donald et al. (2009); Model 1	2 BNs with 14 nodes each (Winbugs)	**CPT**	D,E	1	Population health researcher	Individual meeting	<u>Probability tables</u>		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Drew and Collazo (2012)	BN (Netica)	**DAG and CPT**	D,E,L	4	Biologists („experienced wildlife professionals“)	Individual meetings	• “Discussion interviews” (Drew and Collazo, 2012: 90ff.) • Identification of variables • Probability tables Other • “Image-based interviews” (Drew and Collazo, 2012: 93) • Elicitation of probability classes (low, moderate, high) to preselected potential habitat sites visualized using aerial images		
Florin et al. (2013)	BN with 31 nodes (Netica)	**CPT**	E,S	6 2 2	Technical assistants; Local researchers; Industry players	Unknown (questonnaire)	Frequencies • Example: “Out of n number of farmers how many (x) do you expect to increase their yields?” (Florin et al., 2013: 85) • Elicitation of frequencies for a reduced number of scenarios • Elicitation according to expertise	• Interpolation of other probability values (Cain, 2001)	• Averaging of probability values after the exclusion of some estimates
Grêt-Regamey et al. (2013)	GIS-based BN with 35 nodes (Hugin)	**CPT**	E,S		Local stakeholders Environmental economists	Individual meetings (“expert survey”)	Probability tables • Elicitation of probability values for each state of the 5 nodes		• Averaging of probability values
Haapasaari and Karjalainen (2010)	BDN with 5 nodes	**CPT**			Experts in salmon management in the Baltic Sea	No meeting (questionnaire sent by email)	Other • Selection (ticking) of preferred alternatives, incl. explanation of selections	• Frequency of preferences counted	• Probability distribution smoothed using Dirichlet formula
Haapasaari et al. (2013)	6 BNs	**DAG and CPT**	E,S	1 1 1 1 2	Commercial fisherman; Government officer; Representative of an environmental NGO; Officer of a fishermen’s org.; Researchers	Individual meetings (6 “individual WS”, 4-6 h each)	Probability tables		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consulta-tion format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Hamilton et al. (2007)	BN with 23 nodes (Netica)	**DAG**	E		Group of individuals with specialist scientific, planning and impacts knowledge of *Lyngbya majuscula*	Group meetings (3 WS)	• Identification of a hierarchy of variables • Development of DAG		• Group consensus • Changes made by individuals were revised and confirmed by entire group
		CPT	D,E,M			Group and individual meetings	Probability tables		
Holzkämper et al. (2012)	BN coupled with other models (Netica)	**DAG**	E	9	Experts from different policy groups within the Environment Agency; Researchers	Group meetings	• Identification of variables • Development of DAG		
		CPT	D,E,M	5	Experts in freshwater ecology	Unknown	Weights • Elicitation of relative weights by using a modified version of the method introduced by Das (2004)		
Iqbal and MacLean (2010)	GIS-based BN with 10 nodes (Netica)	**DAG**		6	Experts with >15 years of defoliation prediction experience	Group meetings	• Development of preliminary DAG by one expert which was iteratively revised by the others		
		CPT					Probability tables		
Jensen et al. (2009)	OOBN with 2 classes (Esthauge LIMID Software System)	**CPT**	E,L	9	Experts with specialist knowledge of leg disorders in finishers	Individual meetings	Probability scales • Standardized probability scale from 0 to 100% with verbal expressions ("verbal anchors") added to points and intervals on the scale, using the method introduced by van der Gaag et al. (2002) • Elicitation of values according to expertise		• Averaging of probability values if ≥1 estimates available

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN software)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Johnson et al. (2010)	BN with 29 nodes (Hugin)	**DAG**	E		Cheetah experts Statisticians	Group meeting (4-day WS)	• Definition of variables • Development of DAG		
		CPT	E				Probability tables • Elicitation of some probability values • Elicitation of weights for parent nodes of variables		
Kumar et al. (2012)	BN	**DAG**	E,S	26	Experts in ecology, water science, planning, development, urban design, engineering, social science, and history	Individual meetings	• Development of conceptual networks ("mind maps") by each expert		• Mind maps of experts merged into DAG
		CPT	E,S			Unknown	Weights • Elicitation of relative weights by using a modified version of the method introduced by Das (2004)		• Averaging of probability values
Liu et al. (2013)	BN with 14 nodes (Hugin)	**CPT**	D,E			Unknown	Other • Elicitation of worst-case morbidities and mortality for six diseases	• Estimation of probability values between baseline and worst-case	
McCloskey et al. (2011)	2 GIS-based BNs with 12 and 8 nodes (Netica)	**CPT**	D,E		Several experts	Unknown	Probability tables		• Averaging of probability values
McDowell et al. (2009)	BN with 41 nodes (Netica)	**CPT**	D,E			Unknown	Rankings • Combinations of states of parent nodes ranked from greatest positive to greatest negative effect on the child node (McDowell et al., 2009: 1977)	• Probability values assigned to rankings based on literature and experts • Interpolation of some values (Cain, 2001)	

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Money et al. (2012)	BN with four components (Netica)	**DAG**	E	5 7 3 2	Microbiologists; Ecotoxicologists; Chemists/engineers; Experts in risk analysis	Group meetings (42 meetings)	• Elicitation of four components of the DAG separately from subsets of the domain experts (according to expertise)		• 4 components combined in final DAG
		CPT	E				Frequencies • Example: „Given that A has a value between 0 and 25 and B is 'Low', out of 100 independent experiments, how many times would you expect C to be between 0 and 10?" (p.438) • Application of Noisy-max distributions to complex CPTs by assuming independence of causal influence (ICI) → elicitation of frequencies given the states of one parent node only		
Montewka et al. (2013)	BDN with 35 nodes (Hugin)	**CPT**	E,L	15	Professionals in the field of environmental issues	Group meeting with group discussions (1-day WS)	Probability tables		
Murray et al. (2012)	BN with 8 nodes coupled with other model (Netica)	**DAG**	E	4 1 6	Academics; Land management officer; Landholders with active research or direct experience with lippia management	Group meeting with small group discussions and entire group discussions (2-day WS)	• Identification and ranking of key variables		• Group consensus
		CPT	D,E,M				Probability tables		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Nash et al. (2010)	BN with 31 nodes (Netica)	**DAG**	D,L,S	14	Farmers and farm advisors (WS 1)	Group meetings (2 WS) with group discussions	• Discussion of preliminary DAG (based on data and literature)		
				4	Crop researchers (WS 2)		• Discussion of preliminary DAG (based on data, literature, and previous WS)		
		CPT	D,E			Unknown	Rankings • Combinations of states of parent nodes were ranked from greatest positive to greatest negative effect on the child node	• Probability values assigned to rankings based on information from literature and experts • Interpolation of some values (Cain, 2001)	
Newton et al. (2007); CS 3	3 BNs with 2 nodes (Hugin)	**CPT**	E,L	17	Conservation practitioners	No meeting (questionnaire)	Other • Assessment of effectiveness of 13 methods using a standard scale: -2 (very effective); -1 (effective); 0 (no impact); 1 (ineffective); 2 (very ineffective) representing the states of the child node	• Probability values calculated by counting the questionnaire responses	
Nolivos et al. (2011)	BN with 14 nodes (GeNIe)	**DAG**	E,S		Local government, banana farmers, rural population living near the basin outlet, experts from related fields	Individual meetings	• Identification of variables		
		CPT	D,E			Unknown	Probability tables • Application of Noisy-AND and Noisy-OR approximation by assuming independence of causal influence (ICI) among five parent nodes		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Pellikka et al. (2005)	8 BNs with 22-72 links (FC BeNe)	**DAG**	E	5 2 1	Scientists focusing on wildlife populations; Experts working in the administration of game management; Journalist with academic background in wildlife ecology	Group meeting	• Development of preliminary DAG		
		CPT	E			Individual meeting (5-8 h interviews)	Other • Elicitation of link values for each pair of variables by using a cross-impact matrix with a scale ranging from -1 (complete negative interdependence), 0 (no interdependence), to 1 (complete positive interdependence); • Elicitation of unconditional probability values for PTs		
Penman et al. (2011)	BN with 5 sub-networks (GeNIe)	**DAG**	D,E,L			Individual meetings	• Early versions of DAG discussed with domain experts and BN experts		• Averaging of probability values from 2 WS; DAG and combined probability values assessed by independent reviewer
		CPT	D,E	5	Staff from a governmental fire-suppression agency	Group meeting (1-day WS)	Probability scales • Elicitation of probability values using standardized probability scales that relate verbal expressions to quantitative values using the method from Pollack (2003) as cited in Penman et al. (2011) • Elicitation of probability values for a reduced number of scenarios (135 extreme and mid-range scenarios instead of 375 scenarios)		
				7	Staff from a land-management agency with responsibilities for fire management	Group meeting (1-day WS)			

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	**BN facts (BN soft-ware)**	**Knowledge source**		**Number and background of experts/stakeholders**		**Consultation format**	**Elicitation format**	**Derivation of probability values**	**Combination of DAGs and probability values**
Pike 2004	10 BNs (Hugin)	**DAG**	E	10	Operators at water systems	Individual meetings (interviews)	• Structured interview followed by guided development of DAGs		• DAGs not combined
		CPT	E				Probability scales • Using standardized probability scales that relate verbal expressions to quantitative values using the method from Renooij and Witteman (1999)		• Probability values not averaged
Ren et al. 2008	BN with 11 nodes	**CPT**	E		Experts in offshore safety assessment	Individual meetings (interviews)	Other • Elicitation of conditional fuzzy probabilities by using fuzzy membership functions in the form of triangular fuzzy numbers consisting of the lower least likely value, the most likely value, and the upper least likely value (Ren et al., 2008: 93)	• Transformation of fuzzy values into crisp values with equation (Ren et al., 2008: 97)	
Richards et al. 2013	22 BNs (Netica)	**DAG**	E,S	66	Representatives of government agencies, NGOs and the private sector – working in the field of climate change adaptation management and/or policy development	Group meetings (6 WS with different participants)	• Development of 6 conceptual models with 245 variables on paper and Vensim software • Identification of 22 “priority issues” • Identification of 3 parent nodes for each priority issue and up to 3 parent nodes for each identified parent node by small groups with at least 3 persons		• Probability values not averaged • Integration of values from all stakeholders into one BN with conditioning or auxiliary variables for each child node (Kjaerulff and Madsen, 2008)
		CPT	E,S			Individual meetings during or after WS	Probability tables		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Schmitt and Brugere (2013)	BN with 34 nodes, incl. 9 utility nodes and 25 chance nodes (GeNIe)	**DAG**	E	42	Senior experts in coastal aquaculture from academia, research institutes and industry	No meeting (through email)	• Validation of preliminary DAG by 42 experts • Refinement of DAG by 12 experts		
		CPT	D,E, L	4		Individual meetings (“in-depth dialogue”)	Probability tables • Direct elicitation of probability values for all chance nodes from four experts		• Averaging of probability values
Seidel et al. (2003)	BN with 8 nodes (Hugin)	**CPT**	E	3	Equine clinicians with 10–20 years of practical experience	Individual meetings (interviews)	Probability tables • Questionnaire		• Averaging of probability values
Shenton et al. (2011); ecological sub-model	BN with 20 nodes	**CPT**	D,E, M	6	Fish experts	Individual meetings (interviews)	Probability tables		• Averaging of probability values
Smith et al. (2007)	GIS-based BN with 12 nodes (Netica)	**DAG**	E,L	10 2	Ecologist; Leading experts in the ecology of the Julia Creek dunnart	No meeting (questionnaire survey)	• Review of preliminary DAG (based on literature and feedback from 1 expert) • Review of DAG (based on literature and feedback from 10 ecologists)		• Integration of feedback from 12 experts into final DAG
		CPT	D,E		Ecologist	Individual meetings	Probability tables • Elicitation of values for a reduced number of scenarios (Smith et al., 2007: 338)	• Interpolation of other probability values (Cain, 2001)	
Smith et al. (2012)	BN with 15 nodes (Netica)	**DAG**	E	3 3 3	Local extension officers; Local property managers; Weed ecologists	Group meeting (1 WS)	• Identification of key variables with the help of group engagement techniques (Smith et al., 2012: 820)		
		CPT	E			Unknown	Probability tables • Elicitation of values for a reduced number of scenarios (Smith et al., 2012: 821)	• Interpolation of other probability values (Cain, 2001)	

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	BN facts (BN soft-ware)	Knowledge source		Number and background of experts/stakeholders		Consultation format	Elicitation format	Derivation of probability values	Combination of DAGs and probability values
Tiller et al. (2013)	BN with 15 nodes, incl. 1 auxiliary variable (Netica)	**DAG**	S	10	Local commercial fishermen	Group meeting with group discussions (1 WS)	• Identification of 3 parent nodes of an variable of interest (“Income”) plus identification of up to 3 parent nodes for each parent node • Elicitation of percentages reflecting the proportional influence of parent nodes		• Probability values not averaged • Integration of probability values from all stakeholders into one BN with conditioning or auxiliary variable (Kjaerulff and Madsen, 2008)
		CPT	S	8	Local commercial fishermen	Individual meetings after WS	Probability tables • Elicitation supported by first ranking combinations of states of the parent nodes from most desirable to least desirable		
Troldborg et al. (2013)	BN with 32 nodes and 48 links (Netica)	**DAG**	E		Experts from the fields of risk analysis, modeling, soil science, land use and crop systems	Unknown (3 formal meetings)	• Development of DAG		
		CPT	D,E,L			Unknown	Probability tables		
Uusitalo et al. (2005)	BN with 10 nodes, incl. 2 auxiliary variables (Hugin)	**DAG**	E	5	Salmon experts	Group meeting with individual elicitation of probability values (2-day WS)	• Group discussion: Development of DAG		
		CPT	E				Probability tables • Elicitation of probability values from each expert with questionnaire		• Averaging of probability values
van Dam et al. (2013)	BN with 34 nodes (Netica)	**DAG**	D,E,S		Representatives of the community and NGOs, government officials, “experts” and scientists	Unknown	• Development of DAG based on group discussions with the community, individual interviews and field observations		
		CPT	D,E,S		“experts” and scientists	Group meeting with small group discussions	Probability tables • Elicitation according to interest and expertise		

Table A - 1: List of 50 expert- and stakeholder-based Bayesian Network applications published from 2003-2013 (continued).

Author; Case study (CS)	**BN facts (BN soft-ware)**	**Knowledge source**		**Number and background of experts/stakeholders**		**Consultation format**	**Elicitation format**	**Derivation of probability values**	**Combination of DAGs and probability values**
Vilizzi et al. (2012) (incl. Beesley et al., 2011)	4 BNs with 39, 37, 31 and 31 nodes (Netica)	**DAG**	E,S		Fish experts and managers	Unknown			
		CPT	E	8	Experts in fish ecology and limnology (5-7 experts per BN)	Unknown	Other • Elicitation of graphical relationships in the form of bars in a coordinate system, with states of the parent nodes being represented on the x-axis and states of the child node being represented on the y-axis (see Beesley et al., 2011: 96)	Conversion of graphical relationships into estimated probability ranges and probability values	• Averaging of probability values
Wang et al. (2009a)	BN with 5 interlinked components (Netica)	**DAG**	E,L	14	Local experts with experience in farm management, development and implementation of catchment strategies and biophysical research	Individual meetings (semi-structured interviews)	• Development and Revision of DAG based on expert interviews and scientific literature		
		CPT	D,E				Probability tables • Elicitation of probability values for a reduced number of scenarios	Interpolation of other probability values (Cain, 2001)	
Williams and Cole (2013)	BN with 17 nodes (Netica)	**CPT**	E	3	Experts in blue-green algal blooms	Individual meetings (structured interviews)	Probability tables • Direct elicitation of probability values		• Averaging of probability values

Appendix B Case study NW China: Bayesian Network documentation

Table B - 1: Input used to develop the preliminary Bayesian Networks (Dust BN and Heat BN) which were presented at WS 1.

Nodes in Dust BN and Heat BN		
No.	**Node**	**References/Input**
1	Urban vegetation	Expert interviews 2011; SuMaRiO PhD Seminar 2011
2	Rooftop greening	*
3	Natural peri-urban vegetation	Literature review (Luo et al., 2011)
4	Overgrazing	Literature review (Fang, 2008; Gao and Jing, 2009)
5	Shelterbelt forests	Literature review (Qi, 2009; Yan, 2010)
6	Education	Literature review (Huo, 2009; Pan, 2010; Qi, 2009; Zhou et al., 2010)
7	Human health impacts	Literature review (Pan, 2010; Shi et al., 2000; Zhou et al., 2010)
8	Crop damages	Literature review (Wang and Shi, 2010; Yan, 2010), SuMaRiO PhD Seminar 2011
9	Environmental damages	SuMaRiO PhD Seminar 2011
10	Irrigation needs?	Expert interviews 2011
Additional nodes in Dust BN		
11	Dust weather in oasis town	*
12	Wind soil erosion	Literature review (He et al., 2011)
13	Soil stability	Literature review (He et al., 2011)
14	Soil type/texture	Literature review (He et al., 2011)
15	Soil moisture	Literature review (He et al., 2011; Luo et al., 2011)
16	Regional air temperature	Literature review (Pan, 2010)
17	Precipitation	Literature review (He et al., 2011; Tao, 2009)
18	Ground wind speed	Literature review (He et al., 2011; Luo et al., 2011)
19	Tropospheric wind speed	Input from supervisor
20	Dust filtered	Expert interviews 2011
21	Fine dust filtered	Expert interviews 2011
22	Early warning system	Literature review (Huo, 2009; Pan, 2010; Yan, 2010)
23	Infrastructure damages	Literature review (Huo, 2009; Wang and Shi, 2010)

Table B - 1: Input used to develop the preliminary Bayesian Networks (Dust BN and Heat BN) which were presented at WS 1 (continued).

Additional nodes in Heat BN		
No.	**Node**	**References/Input**
11	Urban heat island in the oasis town	*
12	Regional air temperature	Literature review (Pan, 2010)
13	Cooling effects	*
14	Wind flow	*
15	Wind channels	Literature review (Hu and Li, 2011)
16	Narrow construction of skyscrapers (to create downslope winds)	Literature review (Klimacampus, 2011)
17	Shade	*
18	Evapotranspiration	*
19	Narrow roads & narrow construction	*
20	Heat on roofs	*
21	Light-colored/reflective material	Literature review (Kang et al., 2011; Wang et al., 2009b)
22	Asphalt heat	*
23	Watering roads	Expert interviews 2011
24	Rejected heat	Literature review (Klimacampus, 2011)
25	Air conditioning	SuMaRiO PhD Seminar 2011
26	Improve heat insulation	*
27	Energy consumption	*
28	Industry	Literature review (Kang et al., 2011)

*Nodes without a reference in the right column were either added due to qualitative assumptions, such as "buildings can provide shade in narrow roads", or serve as summary nodes, such as "Cooling effects" or "Wind flow".

Table B - 2: List of nodes of final ESS BN.

Node title	Node name	Node type	No. of states	States
Plant species in peri-urban area	periurban_plants	• Root node • Discrete	11	*Ailanthus altissima (Mill.) Swingle, Elaeagnus augustifolia L., Juglans regia L.,* Lawn, *Malus sieversii (Ledeb.) M. Roem., Morus alba L., Platanus orientalis L., Populus alba L., Populus euphratica* OLIVIER., *Tamarix ramosissima Ledeb., Ulmus pumila L*
Plant species in urban area	urban_plants	• Root node • Discrete	10	*Fraxinus sogdiana Bunge., Juglans regia L., Morus alba L., Platanus orientalis L., Populus alba L., Robinia pseudoacacia L., Salix alba L. Sophora japonica L., Ulmus pumila L., Zizyphus jujuba Mill.*
Vegetation cover in % of urban area	extent_urban_veg	• Root node • Discrete	3	low (<30%), medium (30-45%), high (>45%)
Extent of peri-urban vegetation	extent_periurban_veg	• Root node • Discrete	3	small, medium, large (medium being anchored to current state, low being a decrease, high being an increase)
▲ Plant-specific irrigation needs (urban)	irri_urban_plants	• Discrete	5	very low, low, medium, high, very high
● Irrigation needs in urban area	irri_urban	• Leaf node • Continuous	5	very low, low, medium, high, very high
▲ Plant-specific irrigation needs (peri-urban)	irri_periurban_plants	• Discrete	5	very low, low, medium, high, very high
● Irrigation needs in peri-urban area	irri_periurban	• Leaf node • Continuous	5	very low, low, medium, high, very high
▲ Plant-specific shade	plant_shade	• Discrete	3	low, medium, high
● Shade by urban vegetation	veg_shade	• Continuous	3	low, medium, high
Shade by urban vegetation*	veg_shade2	• Discrete	3	low, medium, high

Table B - 2: List of nodes of final ESS BN (continued).

Node title	Node name	Node type	No. of states	States
▲ Plant-specific soil protection	plant_soil_protection	• Discrete	3	low, medium, high
▲ Plant-specific wind protection	plant_wind_protection	• Discrete	3	low, medium, high
▲ Plant-specific dust filter	plant_dust_filter	• Discrete	3	low, medium, high
● Dust weather mitigation by plants	plant_dust_mit	• Continuous	3	low, medium, high
Dust weather mitigation by plants*	plant_dust_mit2	• Discrete	3	low, medium, high
● Dust weather mitigation by vegetation	veg_dust_mit	• Continuous	3	low, medium, high
Dust weather mitigation by vegetation*	veg_dust_mit2	• Discrete	3	low, medium, high
● Ecosystem services	ESS	• Leaf node • Continuous	3	low, medium, high

▲ Conditional probability table derived from expert estimates

● Conditional probability table built from equation

* not shown in ESS BN that was presented at WS 3; each of these nodes is a copy of its continuous parent node and serves as discrete parent node to its child node (see Chapter 2.2.2)

Table B - 3: Equations used in the final ESS BN.

Node name	Node title	Equation
● Ecosystem services	ESS	ESS (veg_dust_mit2, veg_shade2) = (veg_dust_mit2+veg_shade2)/4
● Shade by urban vegetation	veg_shade	veg_shade (extent_urban_veg, plant_shade) = (extent_urban_veg+plant_shade)/4
● Dust weather mitigation by vegetation	veg_dust_mit	veg_dust_mit (extent_periurban_veg, plant_dust_mit2) = (extent_periurban_veg+plant_dust_mit2)/4
● Dust weather mitigation by plants	plant_dust_mit	plant_dust_mit (plant_dust_filter, plant_soil_protection, plant_wind_protection) = (plant_dust_filter+plant_soil_protection+plant_wind_protection)/6
● Irrigation needs in peri-urban area	irri_periurban	irri_periurban (irri_periurban_plants, extent_periurban_veg) = (irri_periurban_plants+extent_periurban_veg)/6
● Irrigation needs in urban area	irri_urban	irri_urban (irri_urban_plants, extent_urban_veg) = (irri_urban_plants+extent_urban_veg)/6

Tables B-3 to B-9: Conditional probability tables derived from expert estimates

Table B - 4: Conditional probability table "Plant-specific shade" based on weighted average of expert estimates (A,B,C) and "very confident" conversion table.

Node: plant_shade Apply Okay

Chance % Probability Reset Close

Plant species in urban area	low	medium	high
Fraxinus sogdiana Bunge.	5	15	80
Juglans regia L.	5	15	80
Morus alba L.	5	15	80
Platanus orientalis L.	5	15	80
Populus alba L.	5	15	80
Robinia pseudoacacia L.	5	15	80
Salix alba L.	5	15	80
Sophora japonica L.	10	80	10
Ulmus pumila L.	5	15	80
Zizyphus jujuba Mill.	10	80	10

Table B - 5: Conditional probability table “Plant-specific soil protection” based on weighted average of expert estimates (A,B,C) and “very confident” conversion table.

Node: plant_soil_protection | Apply | Okay
Chance | % Probability | Reset | Close

Plant species in peri-urban area	low	medium	high
Ailanthus altissima (Mill.) Swingle	10	80	10
Elaeagnus augustifolia L.	5	15	80
Juglans regia L.	10	80	10
Lawn	5	15	80
Malus sieversii (Ledeb.) M. Roem.	10	80	10
Morus alba L.	5	15	80
Platanus orientalis L.	10	80	10
Populus alba L.	10	80	10
Populus euphratica Olivier	5	15	80
Tamarix ramosissima Ledeb.	5	15	80
Ulmus pumila L.	5	15	80

Table B - 6: Conditional probability table “Plant-specific wind protection” based on weighted average of expert estimates (A,B,C) and “very confident” conversion table.

Node: plant_wind_protection | Apply | Okay
Chance | % Probability | Reset | Close

Plant species in peri-urban area	low	medium	high
Ailanthus altissima (Mill.) Swingle	10	80	10
Elaeagnus augustifolia L.	5	15	80
Juglans regia L.	10	80	10
Lawn	80	15	5
Malus sieversii (Ledeb.) M. Roem.	10	80	10
Morus alba L.	10	80	10
Platanus orientalis L.	5	15	80
Populus alba L.	5	15	80
Populus euphratica Olivier	5	15	80
Tamarix ramosissima Ledeb.	5	15	80
Ulmus pumila L.	5	15	80

Table B - 7: Conditional probability table “Plant-specific dust filter” based on weighted average of expert estimates (A,B,C) and “very confident” conversion table.

Node: plant_dust_filter | Apply | Okay
Chance | % Probability | Reset | Close

Plant species in peri-urban area	low	medium	high
Ailanthus altissima (Mill.) Swingle	10	80	10
Elaeagnus augustifolia L.	5	15	80
Juglans regia L.	5	15	80
Lawn	80	15	5
Malus sieversii (Ledeb.) M. Roem.	5	15	80
Morus alba L.	5	15	80
Platanus orientalis L.	5	15	80
Populus alba L.	5	15	80
Populus euphratica Olivier	5	15	80
Tamarix ramosissima Ledeb.	10	80	10
Ulmus pumila L.	10	80	10

Table B - 8: Conditional probability table "Plant-specific irrigation needs" (peri-urban) based on weighted average of expert estimates (A,B,C) and "very confident" conversion table.

Plant species in peri-urban area	very low	low	medium	high	very high
Ailanthus altissima (Mill.) Swingle	15	80	5	0	0
Elaeagnus augustifolia L.	80	15	5	0	0
Juglans regia L.	0	0	15	80	5
Lawn	0	0	0	10	90
Malus sieversii (Ledeb.) M. Roem.	0	0	5	80	15
Morus alba L.	5	80	15	0	0
Platanus orientalis L.	0	0	5	80	15
Populus alba L.	0	5	80	15	0
Populus euphratica Olivier	90	10	0	0	0
Tamarix ramosissima Ledeb.	90	10	0	0	0
Ulmus pumila L.	90	10	0	0	0

Table B - 9: Conditional probability table "Plant-specific irrigation needs" (urban) based on weighted average of expert estimates (A,B,C) and "very confident" conversion table.

Plant species in urban area	very low	low	medium	high	very high
Fraxinus sogdiana Bunge.	0	5	80	15	0
Juglans regia L.	0	0	15	80	5
Morus alba L.	5	80	15	0	0
Platanus orientalis L.	0	0	5	80	15
Populus alba L.	0	5	80	15	0
Robinia pseudoacacia L.	0	5	80	15	0
Salix alba L.	0	0	5	15	80
Sophora japonica L.	0	5	80	15	0
Ulmus pumila L.	90	10	0	0	0
Zizyphus jujuba Mill.	0	5	80	15	0

Tables B-10 to B-15: Conditional probability tables build from equations

Table B - 10: Conditional probability table "Dust weather mitigation by plants" build from an equation (see Table B - 3).

plant_dust_filter	plant_soil_protection	plant_wind_protection	low	medium	high
low	low	low	100	0	0
low	low	medium	100	0	0
low	low	high	0	100	0
low	medium	low	100	0	0
low	medium	medium	0	100	0
low	medium	high	0	100	0
low	high	low	0	100	0
low	high	medium	0	100	0
low	high	high	0	0	100
medium	low	low	100	0	0
medium	low	medium	0	100	0
medium	low	high	0	100	0
medium	medium	low	0	100	0
medium	medium	medium	0	100	0
medium	medium	high	0	0	100
medium	high	low	0	100	0
medium	high	medium	0	0	100
medium	high	high	0	0	100
high	low	low	0	100	0
high	low	medium	0	100	0
high	low	high	0	0	100
high	medium	low	0	100	0
high	medium	medium	0	0	100
high	medium	high	0	0	100
high	high	low	0	0	100
high	high	medium	0	0	100
high	high	high	0	0	100

Table B - 11: Conditional probability table "Dust weather mitigation by vegetation" build from an equation (see Table B - 3).

Extent of peri-urban vegetation	Dust weather mitigation by plan...	low	medium	high
small	low	100	0	0
small	medium	100	0	0
small	high	0	100	0
medium	low	100	0	0
medium	medium	0	100	0
medium	high	0	0	100
large	low	0	100	0
large	medium	0	0	100
large	high	0	0	100

Table B - 12: Conditional probability table "Shade by urban vegetation" build from an equation (see Table B - 3).

Vegetation cover in % of urban ...	plant_shade	low	medium	high
low (<30%)	low	100	0	0
low (<30%)	medium	100	0	0
low (<30%)	high	0	100	0
medium (30-45%)	low	100	0	0
medium (30-45%)	medium	0	100	0
medium (30-45%)	high	0	0	100
high (>45%)	low	0	100	0
high (>45%)	medium	0	0	100
high (>45%)	high	0	0	100

Table B - 13: Conditional probability table "Irrigation needs in peri-urban area" build from an equation (see Table B - 3).

irri_periurban_plants	Extent of peri-urban vegetation	very low	low	medium	high	very high
very low	small	100	0	0	0	0
very low	medium	100	0	0	0	0
very low	large	0	100	0	0	0
low	small	100	0	0	0	0
low	medium	0	100	0	0	0
low	large	0	0	100	0	0
medium	small	0	100	0	0	0
medium	medium	0	0	100	0	0
medium	large	0	0	0	100	0
high	small	0	0	100	0	0
high	medium	0	0	0	100	0
high	large	0	0	0	0	100
very high	small	0	0	0	100	0
very high	medium	0	0	0	0	100
very high	large	0	0	0	0	100

Table B - 14: Conditional probability table "Irrigation needs in urban area" build from an equation (see Table B - 3).

irri_urban_plants	Vegetation cover in % of urban ...	very low	low	medium	high	very high
very low	low (<30%)	100	0	0	0	0
very low	medium (30-45%)	100	0	0	0	0
very low	high (>45%)	0	100	0	0	0
low	low (<30%)	100	0	0	0	0
low	medium (30-45%)	0	100	0	0	0
low	high (>45%)	0	0	100	0	0
medium	low (<30%)	0	100	0	0	0
medium	medium (30-45%)	0	0	100	0	0
medium	high (>45%)	0	0	0	100	0
high	low (<30%)	0	0	100	0	0
high	medium (30-45%)	0	0	0	100	0
high	high (>45%)	0	0	0	0	100
very high	low (<30%)	0	0	0	100	0
very high	medium (30-45%)	0	0	0	0	100
very high	high (>45%)	0	0	0	0	100

Table B - 15: Conditional probability table “Ecosystem services” build from an equation (see Table B - 3).

Dust weather mitigation by veg...	Shade by urban vegetation	low	medium	high
low	low	100	0	0
low	medium	100	0	0
low	high	0	100	0
medium	low	100	0	0
medium	medium	0	100	0
medium	high	0	0	100
high	low	0	100	0
high	medium	0	0	100
high	high	0	0	100

Appendix C Case study NW China: Workshop materials

Table C - 1 to Table C - 3: Anonymized workshop programmes

Table C - 1: Anonymized programme of the first Workshop, Urumqi, 25th May 2012.

中德学术研讨会

新疆绿洲城市与城郊森林生态系统服务价值

Sino-German Workshop on

Ecosystem Services of Urban and Peri-urban Forests in Oasis Cities of Xinjiang

May 25th, 2012 / 2012 年 5 月 25 日

主办单位/Host：

中国林业科学院新疆分院 / CAF Xinjiang

德国 Eberswalde 应用科技大学 / Eberswalde University for Sustainable Development

新疆大学 / Xinjiang University

协办单位/Co-Organizer：

新疆维吾尔自治区青年科技工作者协会

新疆师范大学 / Xinjiang Normal University

德国法兰克福大学 / Frankfurt University

德国埃希施塔特大学 / KU Eichstätt-Ingolstadt

会议日程表 **Workshop-Programme**
会议地点/Venue： **新疆林科院二楼学术报告厅**（乌鲁木齐市南湖安居南路 191 号） Conference room of CAF Xinjiang (Urumqi Nanhu Anju Nanlu 191)
会议联系人/Contact Person：xxx
会议语言/Conference Language：汉语、德语、英语 (Chinese, German, English)

Table C - 1: Anonymized programme of the first Workshop, Urumqi, 25th May 2012 (continued).

会议日程表 Workshop-Programme	
会议地点/Venue： **新疆林科院二楼学术报告厅**（乌鲁木齐市南湖安居南路 191 号） Conference room of CAF Xinjiang (Urumqi Nanhu Anju Nanlu 191) **会议联系人**/Contact Person：xxx **会议语言**/Conference Language：汉语、德语、英语 (Chinese, German, English)	
2012 年 5 月 25 日，星期五： **Friday, 25. 05.2012：**	
10:00 – 10:10	**开幕式** / Opening of the workshop（主持人：xxx）
10:10 – 10:20	中德合作"塔里木河流域沿河绿洲的可持续管理"项目介绍/SuMaRiO - Introduction to SuMaRiO Project (Sustainable Management of River Oasis along the Tarim River/NW China) 报告人：xxx
10:20 – 10:40	合 影 （Group Photo）
	学术报告/Scientific Presentations （主持人：xxx） **上午主题：城市森林的愿景与挑战** / Visions & challenges for urban forests
10:40 – 11:00	1、干旱区城市绿化生态、经济与人文背景研究一以南疆绿洲城市为例 Urban Greening in Oasis Cities in Southern Xinjiang 报告人：xxx
11:00 – 11:30	2、城市与城郊森林生态系统服务及其评估 Urban and peri-urban forests: Ecosystem services (ESS) and their Valuation 报告人：xxx
11:30 – 11:45	3、柯柯牙防护林工程：历史回顾 / The Kökyar project: a historical review 报告人：xxx
11:45 – 12:00	4、新疆城市绿化 50 年回顾与展望 / History of Urban Greening in Xinjiang 报告人：xxx
12:00 – 12:20	**茶歇/Tea Break**
12:20 – 12:40	5、阿克苏柯柯牙防护林体系的三大效应 Vision for Aksu's urban and peri-urban forests (Experience & Expectation) 报告人：xxx
12:40 – 13:40	6、互动讨论：生态系统服务功能纳入到绿洲城市生态建设的困境 Moderated Discussion: Problems in provisioning key ESS in arid Oasis Cities
13:40 – 15:20	**午 饭 / Lunch**

Table C - 1: Anonymized programme of the first Workshop, Urumqi, 25th May 2012 (continued).

15:20 – 15:30	**下午主题：森林的滞尘及降热效应** / The role of forests in relieving dust & heat stress （**主持人：** xxx）
15:30 – 16:15	1、关于沙尘和热岛效应的问卷 / Questionnaire about dust & heat stress 主持人：Sina Frank
16:15 – 16:35	2、南疆沙尘及炎热天气的负面影响 The impacts of dust & heat problem in Southern Xinjiang 报告人：xxx
16:35 – 17:15	3、贝叶斯网络模型在沙尘天气和城市热岛效应管理方面的应用 Introduction to Bayesian networks 报告人：Sina Frank & xxx
17:15 – 17:45	**茶歇**/Tea Break
17:45 – 18:45	**分组讨论** / Break-out groups: a) 热岛效应问题 / Heat stress （xxx） b) 沙尘问题 / Dust stress （Sina Frank，xxx）
18:45 – 19:15	介绍分组讨论结果 / Presentation of results from Break-out groups
19:15 – 19:25	未来展望 / Outlook （xxx、Sina Frank）
19:25 – 19:40	意见反馈和评估 / Feedback & Evaluation （xxx）
19:40 – 19:50	总结/闭幕词/Wrap-up/closing words（xxx）
20:00	**晚宴** / **Dinner**

Table C - 2: Anonymized programme of the second Workshop, Korla, 10th March 2013.

中德学术研讨会

新疆绿洲城市与城郊森林生态系统服务价值：

森林的滞尘及降热效应

Sino-German Workshop on

Ecosystem services of urban and peri-urban forests in oasis cities of Xinjiang: The role of forests in relieving dust & urban heat

2013年03月10日 / March 10, 2013

中国 · 新疆· 库尔勒 / Korla · Xinjiang · China

Table C - 2: Anonymized programme of the second Workshop, Korla, 10th March 2013 (continued).

主办单位 / Host：

新疆师范大学 / Xinjiang Normal University

法兰克福歌德大学 / Goethe Frankfurt University

协办单位/ Co-Host：

国家林业科学院新疆分院 / China Academy of Forestry Sciences in Xinjiang, CAFS

巴州林业局，野生动植物自然保护管理处/ Bazhou Academy of Forestry, Wild Animals and Plants and Nature Reserve Management Office

会议地点 / Venue：

巴州林业局，野生动植物自然保护管理处/ Bazhou Academy of Forestry, Wild Animals and Plants and Nature Reserve Management Office

会议语言 / Workshop Language：汉语、英语 (Chinese, English)

会议联系人 / Contact Person：xxx

会议日程表 Workshop Programme	
16:00 – 16:10	欢迎致词、讨论会介绍、及讨论会参与者（xxx） Welcome speech, Workshop programme, Introduction of workshop participants (xxx)
16:10 – 16:25	报告（一）：参与者模型在可持续环境管理中的应用（xxx） Presentation 1: Participatory modeling in support of sustainable environmental management (xxx)
16:25 – 16:35	关于沙尘和热岛效应的问卷 Questionnaire on dust weather and urban heat management
16:35 – 16:50	报告（二）：新疆绿洲城市与城郊森林生态系统服务价值：森林的滞尘及降热效应 (xxx) Presentation 2: Ecosystem services of urban and peri-urban forests in oasis cities of Xinjiang: The role of forests in relieving dust & urban heat (xxx)
16:50 – 17:30	报告（三）：贝叶斯网络模型在沙尘天气和城市热岛效应管理方面的应用 (Sina Frank、xxx) Presentation 3: Application of Bayesian networks for dust weather and urban heat management (Sina Frank & xxx)
17:30 – 17:45	**茶歇 Tea Break**
17:45 – 18:15	讨论（一）：城市热岛效应管理的贝叶斯网络 Discussion 1: Bayesian Network on urban heat management
18:15 – 18:45	讨论（二）：沙尘天气管理的贝叶斯网络 Discussion 2: Bayesian Network on dust weather management
18:45 – 18:55	反馈 Feedback
18:55 – 19:00	致谢及下一步研究工作计划（xxx） Thank you and next step (xxx)
19:00	**讨论会结束 & 晚餐 End of Workshop & Dinner**

Table C - 3: Anonymized programme of the third Workshop, Urumqi, 11th March 2014.

中德学术研讨会

新疆绿洲城市与城郊森林生态系统服务价值：

森林的滞尘及降热效应

Sino-German Workshop on

Ecosystem services of urban and peri-urban forests in oasis cities of Xinjiang: The role of forests in relieving dust & urban heat

2014年03月11日 / March 11, 2014, Urumqi

主办单位 / Host：

中国林业科学院新疆分院 / CAF Xinjiang
新疆师范大学 / Xinjiang Normal University
法兰克福歌德大学 / Goethe Frankfurt University

会议地点 / Venue：新疆林科院二楼学术报告厅（乌鲁木齐市南湖安居南路 191 号）
Conference room of CAF Xinjiang
(Urumqi Nanhu Anju Nanlu 191)

会议语言 / Workshop Language：汉语、英语 (Chinese, English)

会议联系人 / Contact Person：xxx

Table C - 3: Anonymized programme of the third Workshop, Korla, 11th March 2014 (continued).

会议日程表 Workshop Programme	
10:15 – 10:25	欢迎致词、讨论会介绍、及讨论会参与者（xxx） Welcome speech, Workshop programme, Introduction of workshop participants (xxx)
10:25 – 10:35	中德合作“塔里木河流域沿河绿洲的可持续管理”项目介绍 SuMaRiO - Introduction to SuMaRiO Project (Sustainable Management of River Oasis along the Tarim River/NW China) (xxx)
10:35 – 11:10	报告（一）：引言：贝叶斯网络 (Sina Frank、xxx、xxx) Presentation 1: Introduction: Bayesian Networks (Sina Frank, xxx & xxx)
11:10 – 11:40	报告（二）：汇报从第一及第二次中德学术讨论会上所获得的结果 (Sina Frank、米日姑•买买提、魏阳) Presentation 2: Results from previous workshops (Sina Frank, xxx & xxx)
11:40 – 12:10	**茶歇 Tea Break**
12:10 – 12:40	报告（三）：引言：贝叶斯决策网络 (Sina Frank、xxx、xxx) Presentation 3: Introduction: Bayesian Decision Networks (Sina Frank, xxx & xxx)
12:40 – 13:10	讨论：贝叶斯网络-贝叶斯决策网络结论 (Sina Frank、xxx、xxx) Discussion: Results of Bayesian Networks and Bayesian Decision Networks (Sina Frank, xxx & xxx)
13:10 – 13:20	讨论评价 Workshop evaluation
13:20 – 13:30	致谢（xxx） Thank you (xxx)
13:30	**讨论会结束 & 午餐 End of Workshop & Lunch**

Figure C-1 to Figure C-2: Results of the workshop evaluations

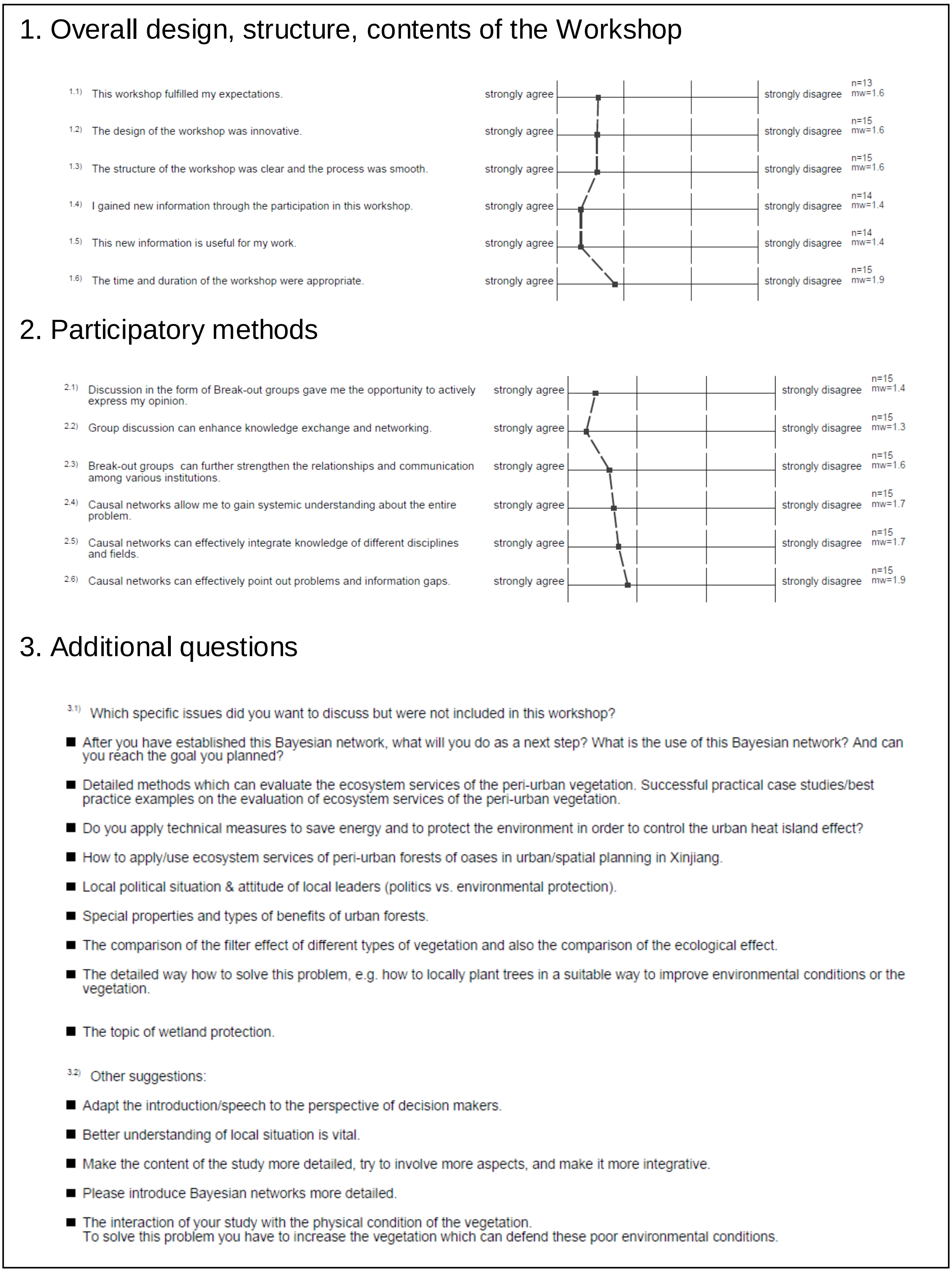


Figure C - 1: Results of the evaluation of WS 1 (n = 15).

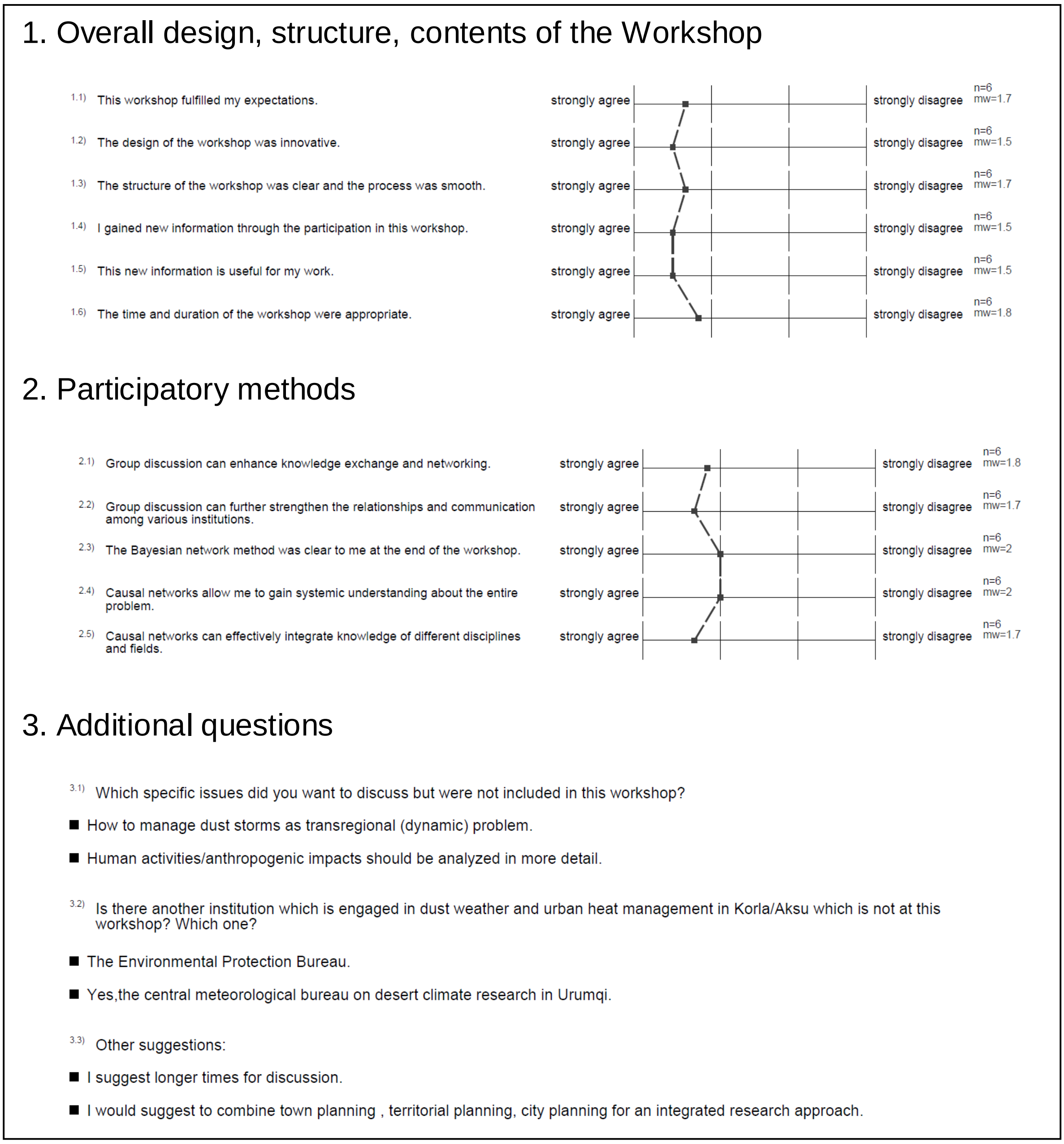
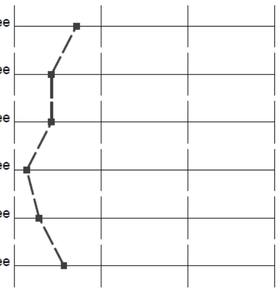


Figure C - 2: Results of the evaluation of WS 2 (n = 6).

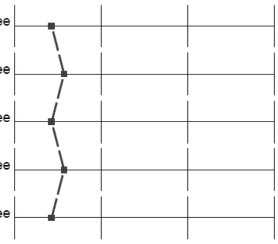
1. Overall design, structure, contents of the Workshop

1.1)	This workshop fulfilled my expectations.	strongly agree – strongly disagree	n=7	mw=1.7
1.2)	The design of the workshop was innovative.	strongly agree – strongly disagree	n=7	mw=1.4
1.3)	The structure of the workshop was clear and the process was smooth.	strongly agree – strongly disagree	n=7	mw=1.4
1.4)	I gained new information through the participation in this workshop.	strongly agree – strongly disagree	n=7	mw=1.1
1.5)	This new information is useful for my work.	strongly agree – strongly disagree	n=7	mw=1.3
1.6)	The time and duration of the workshop were appropriate.	strongly agree – strongly disagree	n=7	mw=1.6



2. Participatory methods

2.1)	Group discussion can enhance knowledge exchange and networking.	strongly agree – strongly disagree	n=7	mw=1.4
2.2)	Group discussion can further strengthen the relationship and communication among various institutions.	strongly agree – strongly disagree	n=7	mw=1.6
2.3)	The Bayesian network method was clear to me at the end of the workshop.	strongly agree – strongly disagree	n=7	mw=1.4
2.4)	Causal networks allow me to gain systemic understanding about the entire problem.	strongly agree – strongly disagree	n=7	mw=1.6
2.5)	Causal networks can effectively integrate knowledge of different disciplines and fields.	strongly agree – strongly disagree	n=7	mw=1.4



3. Additional questions

3.1) Which specific issues did you want to discuss but were not included in this workshop?

- SuMaRiO is getting farther and farther away from Xinjiang University.
- The contents of the Bayesian Network and my expectations.
- The correlation between cost-effectiveness of varieties of economic forests and ecological forests.
- When we discussed conditional probabilities, we should have better explained the relation between ecological principles ("why") and causality in a more visual way.

3.2) Is there another institute which is engaged in dust weather and urban heat management in Korla/Aksu which is not present at this workshop? Which one?

- Land Resources Bureau, Environment Protection Bureau, Urban Planning Bureau.
- Xinjiang Institute for Desert Meteorology, Xinjiang Agricultural Meteorological Observatory.
- Xinjiang Institute of Desert Meteorology.

3.3) Other suggestions:

- When we discuss the management of the urban heat island effect, we should also invite experts from urban planning and housing construction.

Figure C - 3: Results of the evaluation of WS 3 (n = 7).

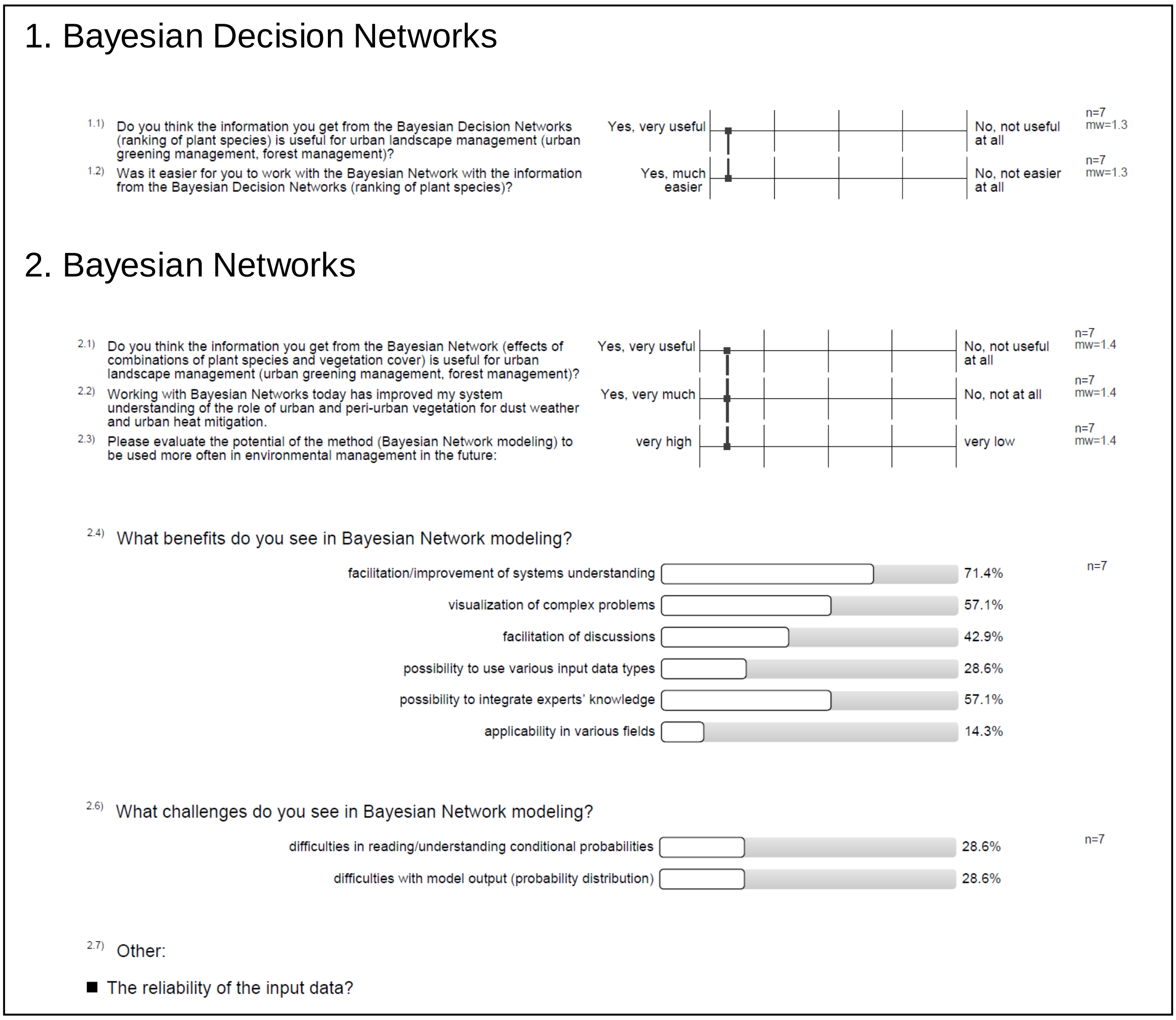


Figure C - 4: Results of the evaluation of Bayesian Networks and Bayesian Decision Networks during WS 3 (n = 7).

Appendix D Case study NW China: Expert elicitation materials

Table D - 1: Estimates on characteristics of peri-urban plant species elicited from three expert groups (A,B,C).

Plant species in peri-urban area		Irrigation needs	Soil stability	Wind protection	Dust filter
		(between 0 - 1) 1 highest need 0 lowest need	very high +++ (3) high ++ (2) rather high + (1) low – (0)		
1	臭椿 *Ailanthus altissima (M.) Swing.*	A: 0.45	A: 1	A: 1	A: 1
		B: 0.1	B: 2	B: 2	B: 2
		C: 0.2	C: 1	C: 1	C: 2
2	沙枣 *Elaeagnus augustifolia L.*	A: 0.3	A: 2	A: 3	A: 2
		B: 0.1	B: 3	B: 3	B: 2
		C: 0	C: 2	C: 2	C: 3
3	核桃 *Juglans regia L.*	A: 0.4	A: 2	A: 2	A: 1
		B: 0.6	B: 2	B: 2	B: 3
		C: 0.7	C: 1	C: 2	C: 2
4	草地 Lawn	A: 1	A: 3	A: 0	A: 0
		B: 1	B: 3	B: 2	B: 0
		C: 1	C: 2	C: 0	C: 1
5	苹果 *Malus sieversii (Ldb.) M. Roem*	A: 0.7	A: 1	A: 1	A: 1
		B: 0.8	B: 2	B: 2	B: 3
		C: 0.9	C: 1	C: 2	C: 3
6	桑树 *Morus alba*	A: 0.3	A: 2	A: 2	A: 2
		B: 0.4	B: 3	B: 2	B: 3
		C: 0.4	C: 2	C: 2	C: 2
7	法国梧桐 *Platanus orientalis L.*	A: 0.6	A: 1	A: 2	A: 1
		B: 0.6	B: 2	B: 3	B: 3
		C: 1	C: 1	C: 2	C: 2
8	新疆杨 *Populus alba*	A: 0.35	A: 2	A: 2	A: 3
		B: 0.5	B: 2	B: 3	B: 3
		C: 0.9	C: 2	C: 2	C: 3
9	胡杨 *Populus euphratica*	A: 0.1	A: 3	A: 3	A: 3
		B: 0	B: 3	B: 3	B: 3
		C: 0.2	C: 2	C: 2	C: 2
10	多枝柽柳 *Tamarix ramosissima Ledeb.*	A: 0	A: 3	A: 2	A: 2
		B: 0	B: 3	B: 3	B: 0
		C: 0	C: 2	C: 2	C: 2
11	白榆 *Ulmus pumila L.*	A: 0.2	A: 2	A: 2	A: 2
		B: 0.3	B: 3	B: 3	B: 2
		C: 0	C: 2	C: 2	C: 2
How confident are you with your estimates? (per column) ++ very confident + rather confident - rather unconfident -- very unconfident		A: +	A: +	A: +	A: +
		B: ++	B: ++	B: ++	B: ++
		C: +	C: +	C: ++	C: ++

Table D - 2: Estimates on characteristics of urban plant species elicited from three expert groups (A,B,C).

Plant species in urban area		Irrigation needs (between 0 - 1) 1 highest need 0 lowest need	Provision of shade very high +++ (3) high ++ (2) rather high + (1) low – (0)
1	小叶白蜡 *Fraxinus sogdiana Bunge.*	A: 0.6	A: 2
		B: 0.5	B: 3
		C: 0.6	C: 2
2	核桃 *Juglans regia L.*	A: 0.7	A: 1
		B: 0.6	B: 3
		C: 0.7	C: 2
3	桑树 *Morus alba*	A: 0.5	A: 3
		B: 0.3	B: 2
		C: 0.4	C: 2
4	法国梧桐 *Platanus orientalis L.*	A: 0.8	A: 1
		B: 0.6	B: 3
		C: 1	C: 3
5	新疆杨 *Populus alba*	A: 0.3	A: 2
		B: 0.6	B: 3
		C: 0.9	C: 3
6	刺槐 *Robinia pseudoacacia L.*	A: 0.6	A: 2
		B: 0.5	B: 3
		C: 0.5	C: 2
7	白柳 *Salix alba L.*	A: 0.65	A: 2
		B: 1	B: 3
		C: 0.7	C: 2
8	槐树/国槐 *Sophora japonica L.*	A: 0.65	A: 2
		B: 0.5	B: 3
		C: 0.5	C: 1
9	白榆 *Ulmus pumila L.*	A: 0	A: 3
		B: 0	B: 3
		C: 0	C: 2
10	枣树 *Zizyphus jujuba Mill.*	A: 0.5	A: 2
		B: 0.6	B: 2
		C: 0.4	C: 1
How confident are you with your estimates? (per column) ++ very confident + rather confident - rather unconfident -- very unconfident		A: +	A: +
		B: ++	B: ++
		C: +	C: ++

Table D - 3: Calculation of weighted average values of estimates on characteristics of peri-urban plant species elicited from expert groups A, B, and C.

	Plant species in peri-urban area	Irrigation needs 1 highest need 0 lowest need	Soil stability	Wind protection	Dust filter
			very high +++ (3), high ++ (2), rather high + (1), low – (0)		
1	臭椿 *Ailanthus altissima (M.) Swing.*	A: 0.45 x 2 = 0.9	A: 1 x 2 = 2	A: 1 x 2 = 2	A: 1 x 2 = 2
		B: 0.1 x 3 = 0.3	B: 2 x 3 = 6	B: 2 x 3 = 6	B: 2 x 3 = 6
		C: 0.2 x 2 = 0.4	C: 1 x 2 = 2	C: 1 x 3 = 3	C: 2 x 3 = 6
		∑ = 1.6	∑ = 10	∑ = 11	∑ = 14
		1.6 / 7 = 0.23	10 / 7 = 1.43	11 / 8 = 1.38	14 / 8 = 1.75
2	沙枣 *Elaeagnus augustifolia L.*	A: 0.3 x 2 = 0.6	A: 2 x 2 = 4	A: 3 x 2 = 6	A: 2 x 2 = 4
		B: 0.1 x 3 = 0.3	B: 3 x 3 = 9	B: 3 x 3 = 9	B: 2 x 3 = 6
		C: 0 x 2 = 0	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 3 x 3 = 9
		∑ = 0.9	∑ = 17	∑ = 21	∑ = 19
		0.9 / 7 = 0.13	17 / 7 = 2.43	21 / 8 = 2.63	19 / 8 = 2.38
3	核桃 *Juglans regia L.*	A: 0.4 x 2 = 0.8	A: 2 x 2 = 4	A: 2 x 2 = 4	A: 1 x 2 = 2
		B: 0.6 x 3 = 1.8	B: 2 x 3 = 6	B: 2 x 3 = 6	B: 3 x 3 = 9
		C: 0.7 x 2 = 1.4	C: 1 x 2 = 2	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 4	∑ = 12	∑ = 16	∑ = 17
		4 / 7 = 0.57	12 / 7 = 1.71	16 / 8 = 2	17 / 8 = 2.13
4	草地 Lawn	A: 1 x 2 = 2	A: 3 x 2 = 6	A: 0 x 2 = 0	A: 0 x 2 = 0
		B: 1 x 3 = 3	B: 3 x 3 = 9	B: 2 x 3 = 6	B: 0 x 3 = 0
		C: 1 x 2 = 2	C: 2 x 2 = 4	C: 0 x 3 = 0	C: 1 x 3 = 3
		∑ = 7	∑ = 19	∑ = 6	∑ = 3
		7 / 7 = 1	19 / 7 = 2.71	6 / 8 = 0.75	3 / 8 = 0.38
5	苹果 *Malus sieversii (Ldb.) M. Roem*	A: 0.7 x 2 = 1.4	A: 1 x 2 = 2	A: 1 x 2 = 2	A: 1 x 2 = 2
		B: 0.8 x 3 = 2.4	B: 2 x 3 = 6	B: 2 x 3 = 6	B: 3 x 3 = 9
		C: 0.9 x 2 = 1.8	C: 1 x 2 = 2	C: 2 x 3 = 6	C: 3 x 3 = 9
		∑ = 5.6	∑ = 10	∑ = 14	∑ = 20
		5.6 / 7 = 0.8	10 / 7 = 1.43	14 / 8 = 1.75	20 / 8 = 2.5
6	桑树 *Morus alba*	A: 0.3 x 2 = 0.6	A: 2 x 2 = 4	A: 2 x 2 = 4	A: 2 x 2 = 4
		B: 0.4 x 3 = 1.2	B: 3 x 3 = 9	B: 2 x 3 = 6	B: 3 x 3 = 9
		C: 0.4 x 2 = 0.8	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 2.6	∑ = 17	∑ = 16	∑ = 19
		2.6 / 7 = 0.37	17 / 7 = 2.43	16 / 8 = 2	19 / 8 = 2.38

Table D - 3: Calculation of weighted average values of estimates on characteristics of peri-urban plant species elicited from expert groups A, B, and C (continued).

	Plant species in peri-urban area	Irrigation needs 1 highest need 0 lowest need	Soil stability	Wind protection	Dust filter
			very high +++ (3), high ++ (2), rather high + (1), low – (0)		
7	法国梧桐 *Platanus orientalis L.*	A: 0.6 x 2 = 1.2	A: 1 x 2 = 2	A: 2 x 2 = 4	A: 1 x 2 = 2
		B: 0.6 x 3 = 1.8	B: 2 x 3 = 6	B: 3 x 3 = 9	B: 3 x 3 = 9
		C: 1 x 2 = 2	C: 1 x 2 = 2	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 5	∑ = 10	∑ = 19	∑ = 17
		5 / 7 = 0.71	10 / 7 = 1.43	19 / 8 = 2.38	17 / 8 = 2.13
8	新疆杨 *Populus alba*	A: 0.35 x 2 = 0.7	A: 2 x 2 = 4	A: 2 x 2 = 4	A: 3 x 2 = 6
		B: 0.5 x 3 = 1.5	B: 2 x 3 = 6	B: 3 x 3 = 9	B: 3 x 3 = 9
		C: 0.9 x 2 = 1.8	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 3 x 3 = 9
		∑ = 4	∑ = 14	∑ = 19	∑ = 24
		4 / 7 = 0.57	14 / 7 = 2	19 / 8 = 2.38	24 / 8 = 3
9	胡杨 *Populus euphratica*	A: 0.1 x 2 = 0.2	A: 3 x 2 = 6	A: 3 x 2 = 6	A: 3 x 2 = 6
		B: 0 x 3 = 0	B: 3 x 3 = 9	B: 3 x 3 = 9	B: 3 x 3 = 9
		C: 0.2 x 2 = 0.4	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 0.6	∑ = 19	∑ = 21	∑ = 21
		0.6 / 7 = 0.09	19 / 7 = 2.71	21 / 8 = 2.63	21 / 8 = 2.63
10	多枝柽柳 *Tamarix ramosissima Ledeb.*	A: 0 x 2 = 0	A: 3 x 2 = 6	A: 2 x 2 = 4	A: 2 x 2 = 4
		B: 0 x 3 = 0	B: 3 x 3 = 9	B: 3 x 3 = 9	B: 0 x 3 = 0
		C: 0 x 2 = 0	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 0	∑ = 19	∑ = 19	∑ = 10
		0 / 7 = 0	19 / 7 = 2.71	19 / 8 = 2.38	10 / 8 = 1.25
11	白榆 *Ulmus pumila L.*	A: 0.2 x 2 = 0.4	A: 2 x 2 = 4	A: 2 x 2 = 4	A: 2 x 2 = 4
		B: 0.3 x 3 = 0.9	B: 3 x 3 = 9	B: 3 x 3 = 9	B: 2 x 3 = 6
		C: 0 x 2 = 0	C: 2 x 2 = 4	C: 2 x 3 = 6	C: 2 x 3 = 6
		∑ = 1.3	∑ = 17	∑ = 19	∑ = 16
		1.3 / 7 = 0.19	17 / 7 = 2.43	19 / 8 = 2.38	16 / 8 = 2
How confident are you with your estimates? (per column) ++ very confident (x3) + rather confident (x2) - rather unconfident (x1) -- very unconfident (x0)		A: +(x 2)	A: +(x 2)	A: +(x 2)	A: +(x 2)
		B: ++ (x 3)	B: ++ (x 3)	B: ++ (x 3)	B: ++ (x 3)
		C: +(x 2)	C: +(x 2)	C: ++ (x 3)	C: ++ (x 3)

Table D - 4: Calculation of weighted average values of estimates on characteristics of urban plant species elicited from expert groups A, B, and C.

Plant species in urban area		Irrigation needs (between 0 - 1) 1 highest need 0 lowest need	Provision of shade very high +++ (3) high ++ (2) rather high + (1) low – (0)
1	小叶白蜡 *Fraxinus sogdiana Bunge.*	A: 0.6 x 2 = 1.2	A: 2 x 2 = 4
		B: 0.5 x 3 = 1.5	B: 3 x 3 = 9
		C: 0.6 x 2 = 1.2	C: 2 x 3 = 6
		∑ = 3.9	∑ = 19
		3.9 / 7 = 0.56	19 / 8 = 2.38
2	核桃 *Juglans regia L.*	A: 0.7 x 2 = 1.4	A: 1 x 2 = 2
		B: 0.6 x 3 = 1.8	B: 3 x 3 = 9
		C: 0.7 x 2 = 1.4	C: 2 x 3 = 6
		∑ = 4.6	∑ = 17
		4.6 / 7 = 0.66	17 / 8 = 2.13
3	桑树 *Morus alba*	A: 0.5 x 2 = 1	A: 3 x 2 = 6
		B: 0.3 x 3 = 0.9	B: 2 x 3 = 6
		C: 0.4 x 2 = 0.8	C: 2 x 3 = 6
		∑ = 2.7	∑ = 18
		2.7 / 7 = 0.39	18 / 8 = 2.25
4	法国梧桐 *Platanus orientalis L.*	A: 0.8 x 2 = 1.6	A: 1 x 2 = 2
		B: 0.6 x 3 =1.8	B: 3 x 3 = 9
		C: 1 x 2 = 2	C: 3 x 3 = 9
		∑ = 5.4	∑ = 20
		5.4 / 7 = 0.77	20 / 8 = 2.5
5	新疆杨 *Populus alba*	A: 0.3 x 2 = 0.6	A: 2 x 2 = 4
		B: 0.6 x 3 = 1.8	B: 3 x 3 = 9
		C: 0.9 x 2 = 1.8	C: 3 x 3 = 9
		∑ = 4.2	∑ = 22
		4.2 / 7 = 0.6	22 / 8 = 2.75
6	刺槐 *Robinia pseudoacacia L.*	A: 0.6 x 2 = 1.2	A: 2 x 2 = 4
		B: 0.5 x 3 = 1.5	B: 3 x 3 = 9
		C: 0.5 x 2 = 1	C: 2 x 3 = 6
		∑ = 3.7	∑ = 19
		3.7 / 7 = 0.53	19 / 8 = 2.38
7	白柳 *Salix alba L.*	A: 0.65 x 2 = 1.3	A: 2 x 2 = 4
		B: 1 x 3 = 3	B: 3 x 3 = 9
		C: 0.7 x 2 = 1.4	C: 2 x 3 = 6
		∑ = 5.7	∑ = 19
		5.7 / 7 = 0.81	19 / 8 = 2.38
8	槐树/国槐 *Sophora japonica L.*	A: 0.65 x 2 = 1.3	A: 2 x 2 = 4
		B: 0.5 x 3 = 1.5	B: 3 x 3 = 9
		C: 0.5 x 2 = 1	C: 1 x 3 = 3
		∑ = 3.8	∑ = 16
		3.8 / 7 = 0.54	16 / 8 = 2
9	白榆 *Ulmus pumila L.*	A: 0 x 2 = 0	A: 3 x 2 = 6
		B: 0 x 3 = 0	B: 3 x 3 = 9
		C: 0 x 2 = 0	C: 2 x 3 = 6
		∑ = 0	∑ = 21
		0 / 7 = 0	21 / 8 = 2.63
10	枣树 *Zizyphus jujuba Mill.*	A: 0.5 x 2 = 1	A: 2 x 2 = 4
		B: 0.6 x 3 = 1.8	B: 2 x 3 = 6
		C: 0.4 x 2 = 0.8	C: 1 x 3 = 3
		∑ = 3.6	∑ = 13
		3.6 / 7 = 0.51	13 / 8 = 1.63

Table D - 4: Calculation of weighted average values of estimates on characteristics of urban plant species elicited from expert groups A, B, and C (continued).

Plant species in urban area	Irrigation needs (between 0 - 1) 1 highest need 0 lowest need	Provision of shade very high +++ (3) high ++ (2) rather high + (1) low – (0)
How confident are you with your estimates? (per column) ++ very confident (x3) + rather confident (x2) - rather unconfident (x1) -- very unconfident (x0)	A: + (x2)	A: + (x2)
	B: ++ (x3)	B: ++ (x3)
	C: + (x2)	C: ++(x3)

Table D - 5: Weighted average values of estimates on characteristics of peri-urban plant species elicited from expert groups A, B, and C.

Plant species in peri-urban area		Irrigation needs	Soil stability	Wind protection	Dust filter
		(between 0 - 1) 1 highest need 0 lowest need	very high +++ (3) high ++ (2) rather high + (1) low – (0)		
1	臭椿 *Ailanthus altissima (M.) Swing.*	0.23	1.43	1.38	1.75
2	沙枣 *Elaeagnus augustifolia L.*	0.13	2.43	2.63	2.38
3	核桃 *Juglans regia L.*	0.57	1.71	2	2.13
4	草地 Lawn	1	2.71	0.75	0.38
5	苹果 *Malus sieversii (Ldb.) M. Roem*	0.8	1.43	1.75	2.5
6	桑树 *Morus alba*	0.37	2.43	2	2.38
7	法国梧桐 *Platanus orientalis L.*	0.71	1.43	2.38	2.13
8	新疆杨 *Populus alba*	0.57	2	2.38	3
9	胡杨 *Populus euphratica*	0.09	2.71	2.63	2.63
10	多枝柽柳 *Tamarix ramosissima Ledeb.*	0	2.71	2.38	1.25
11	白榆 *Ulmus pumila L.*	0.19	2.43	2.38	2
How confident are you with your estimates? (per column) ++ very confident + rather confident - rather unconfident -- very unconfident		A: + B: ++ C: +	A: + B: ++ C: +	A: + B: ++ C: ++	A: + B: ++ C: ++

Table D - 6: Weighted average values of estimates on characteristics of urban plant species elicited from expert groups A, B, and C

Plant species in urban area		Irrigation needs (between 0 - 1) 1 highest need 0 lowest need	Provision of shade very high +++ (3) high ++ (2) rather high + (1) low – (0)
1	小叶白蜡 *Fraxinus sogdiana Bunge.*	0.56	2.38
2	核桃 *Juglans regia L.*	0.66	2.13
3	桑树 *Morus alba*	0.39	2.25
4	法国梧桐 *Platanus orientalis L.*	0.77	2.5
5	新疆杨 *Populus alba*	0.6	2.75
6	刺槐 *Robinia pseudoacacia L.*	0.53	2.38
7	白柳 *Salix alba L.*	0.81	2.38
8	槐树/国槐 *Sophora japonica L.*	0.54	2
9	白榆 *Ulmus pumila L.*	0	2.63
10	枣树 *Zizyphus jujuba Mill.*	0.51	1.63
How confident are you with your estimates? (per column) ++ very confident + rather confident - rather unconfident -- very unconfident		A: + B: ++ C: +	A: + B: ++ C: ++

Table D - 7: Calculation of average irrigation need for 5 urban and peri-urban plant species for which two values were elicited.

Plant species	Irrigation need elicited (peri-urban)	Irrigation need elicited (urban)	Average value
核桃 *Juglans regia L.*	0.57	0.66	0.62
桑树 *Morus alba*	0.37	0.39	0.38
法国梧桐 *Platanus orientalis L.*	0.71	0.77	0.74
新疆杨 *Populus alba*	0.57	0.6	0.59
白榆 *Ulmus pumila L.*	0.19	0	0.01

Table D - 8: Utility table of "Irrigation needs" in the Dust BDN.

Plant species in peri-urban area	Irrigation needs (=costs)
Ailanthus altissima (Mill.) Swingle	-0.23
Elaeagnus augustifolia L.	-0.13
Juglans regia L.	-0.62
Lawn	-1
Malus sieversii (Ledeb.) M. Roem.	-0.8
Morus alba L.	-0.38
Platanus orientalis L.	-0.74
Populus alba L.	-0.59
Populus euphratica Olivier	-0.09
Tamarix ramosissima Ledeb.	0
Ulmus pumila L.	-0.01

Table D - 9: Standardization of values to be used in the utility table "irrigation needs" of the Shade BDN.

Plant species	Irrigation needs	Irrigation needs/0.81	Irrigation need in Shade BDN
Fraxinus sogdiana Bunge.	0.56	0.69	-0.69
Juglans regia L. (Avg)	0.62	0.77	-0.77
Morus alba L. (Avg)	0.38	0.47	-0.47
Platanus orientalis L. (Avg)	0.74	0.91	-0.91
Populus alba L. (Avg)	0.59	0.73	-0.73
Robinia pseudoacacia L.	0.53	0.65	-0.65
Salix alba L.	0.81	1	-1
Sophora japonica L.	0.54	0.67	-0.67
Ulmus pumila L. (Avg)	0.01	0.01	0
Zizyphus jujuba Mill.	0.51	0.63	-0.63

The highest "irrigation needs" value (*Salix alba L.*, 0.81) was set to 1; the other values were divided by 0.81 accordingly. The lowest "irrigation needs" value (Ulmus pumila L. (Avg), 0.01) was rounded to 0. This way, the irrigation needs of the plant species ranged from 0 to 1 and could be entered into the utility table (see Table D - 10).

Table D - 10: Utility table "Irrigation needs" of the Shade BDN.

Plant species in urban area	Irrigation needs (= costs)
Fraxinus sogdiana Bunge.	-0.69
Juglans regia L.	-0.77
Morus alba L.	-0.47
Platanus orientalis L.	-0.91
Populus alba L.	-0.73
Robinia pseudoacacia L.	-0.65
Salix alba L.	-1
Sophora japonica L.	-0.67
Ulmus pumila L.	0
Zizyphus jujuba Mill.	-0.63

Appendix E Case study NW China: Conversion tables

Table E - 1: Conversion tables for values between 0-1 for nodes with 5 states for four levels of confidence in experts' estimates. ("very unconfident", "rather unconfident", "rather confident", and "very confident").

very unconfident	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
0-0.1	60	40	0	0	0
0.11-0.2	50	30	20	0	0
0.21-0.3	30	50	20	0	0
0.31-0.4	20	50	30	0	0
0.41-0.5	0	30	50	20	0
0.51-0.6	0	20	50	30	0
0.61-0.7	0	0	30	50	20
0.71-0.8	0	0	20	50	30
0.81-0.9	0	0	20	30	50
0.91-1	0	0	0	40	60
rather unconfident	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
0-0.1	70	30	0	0	0
0.11-0.2	60	25	15	0	0
0.21-0.3	25	60	15	0	0
0.31-0.4	15	60	25	0	0
0.41-0.5	0	25	60	15	0
0.51-0.6	0	15	60	25	0
0.61-0.7	0	0	25	60	15
0.71-0.8	0	0	15	60	25
0.81-0.9	0	0	15	25	60
0.91-1	0	0	0	30	70
rather confident	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
0-0.1	80	20	0	0	0
0.11-0.2	70	20	10	0	0
0.21-0.3	20	70	10	0	0
0.31-0.4	10	70	20	0	0
0.41-0.5	0	20	70	10	0
0.51-0.6	0	10	70	20	0
0.61-0.7	0	0	20	70	10
0.71-0.8	0	0	10	70	20
0.81-0.9	0	0	10	20	70
0.91-1	0	0	0	20	80
very confident	very low (0-0.2)	low (0.21-0.4)	medium (0.41-0.6)	high (0.61-0.8)	very high (0.81-1)
0-0.1	90	10	0	0	0
0.11-0.2	80	15	5	0	0
0.21-0.3	15	80	5	0	0
0.31-0.4	5	80	15	0	0
0.41-0.5	0	15	80	5	0
0.51-0.6	0	5	80	15	0
0.61-0.7	0	0	15	80	5
0.71-0.8	0	0	5	80	15
0.81-0.9	0	0	5	15	80
0.91-1	0	0	0	10	90

Table E - 2: Conversion tables for values between 0-3 for nodes with 3 states for four levels of confidence in experts' estimates.

("very unconfident", "rather unconfident", "rather confident", and "very confident").

very unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	50	30	20
1.1-2	25	50	25
2.1-3	20	30	50
rather unconfident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	60	25	15
1.1-2	20	60	20
2.1-3	15	25	60
rather confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	70	20	10
1.1-2	15	70	15
2.1-3	10	20	70
very confident	low (0-1)	medium (1.1-2)	high (2.1-3)
0-1	80	15	5
1.1-2	10	80	10
2.1-3	5	15	80

Appendix F   Case study NW China: Miscellaneous

Table F - 1: References for violent incidents in Xinjiang, 2011-07 – 2014-06. (see Figure 17).

Date of incident	Location	Number of people		References
		injured	dead	
2011-07-18	Hotan		14	BBC News (2011a)
2011-07-30	Kashgar	28	8	BBC News (2011b), BBC News (2011c), BBC News (2011d)
2011-07-31	Kashgar	12	13	
2011-12-28	Hotan prefecture	5	8	BBC News (2011e)
2012-02-28	Kashgar prefecture		20	BBC News (2012a), BBC News (2012b)
2012-06-07	Hotan	17		BBC News (2012c)
2013-03-07	Korla	8	4	BBC News (2013a)
2013-04-23	Kashgar prefecture		21	BBC News (2013b)
2013-06-26	Turpan prefecture		35	BBC News (2013c), BBC News (2013d)
2013-11-17	Kashgar prefecture	2	11	BBC News (2013e)
2013-12-15	Kashgar		16	BBC News (2013f)
2013-12-30	Kashgar prefecture		8	BBC News (2013g)
2014-01-24	Aksu prefecture		12	BBC News (2014a)
2014-02-14	Aksu prefecture	4	11	BBC News (2014b)
2014-03-17	Urumqi		2	BBC News (2014c)
2014-04-30	Urumqi	79	3	BBC News (2014d)
2014-05-22	Urumqi	90	39	BBC News (2014e), BBC News (2014f)
2014-06-21	Kashgar prefecture	8	13	BBC News (2014g)

Appendix G Curriculum Vitae

Personal information

Name:	FRANK, Sina Kai
Date of birth:	6th October 1984
Place of birth:	Mettingen, Germany
Nationality:	German

Education and training

September 2010 – May 2011	**Deutsches Institut für Entwicklungspolitik (DIE)/German Development Institute, Bonn, Germany** - Postgraduate Training Programme for Development Cooperation - Member of an interdisciplinary research team conducting a study on "Reducing Emissions from Deforestation and Degradation (REDD) in Peru – A Challenge to Social Inclusion and Multi-level Governance" (Team leader: Dr. Fariborz Zelli)
October 2007 – August 2010	**University of Duisburg-Essen, Germany** - Master of Arts in "Contemporary East Asian Studies" - Thesis: "China's Consumption beyond Carrying Capacity: Social and environmental implications for China and natural resource exporting nations" (Supervisors: Prof. Dr. Markus Taube/Prof. Dr. Werner Pascha)
October 2004 – September 2007	**University of Osnabrück, Germany** - Bachelor of Arts in Geography and History - Thesis: "Urbanisierung und Verwundbarkeit in Indonesien: Das Hochwasser in Jakarta, Februar 2007" (engl.: "Urbanization and Vulnerability in Indonesia: The Jakarta Flood, February 2007") (Supervisors: Prof. Dr. Britta Klagge/Dr. Carsten Felgentreff)
June 2004	**Ratsgymnasium Osnabrück, Germany** - Bilingual final secondary-school examinations (Bilinguales Abitur) - Accelerated school year (2000/2001) - One-year student exchange in Malaysia (2001/2002)

Work experience

November 2014 – present	**Research associate at the Department of Geography, University of Cambridge, United Kingdom** - Early Career Research Fellowship of the Ecosystem Services for Poverty Alleviation (ESPA) Programme funded by DFID, ESRC and NERC - Project title: "Ecosystem Services and Disaster Risks in the Western Himalayas: An integrated participatory modelling approach using Bayesian Networks"
June 2011 – July 2014	**Research associate (Ph.D. student) at the Institute of Physical Geography, Goethe University Frankfurt, Germany** - Involved in the SuMaRiO-Project ("Sustainable Management of River Oases along the Tarim River, China") funded by BMBF - Thesis: Expert-based Bayesian Network modeling for environmental management (Supervisors: Prof. Dr. Petra Döll/ Prof. Dr. Martin Welp)
September – November 2013	**Research stay at CSIRO Land and Water, Canberra, Australia** - Development of a Bayesian Network on ecosystem services of environmental flows in the Murray-Darling Basin, Australia (Supervisor: Dr. Carmel Pollino)
August 2009 – August 2010; September 2008 – February 2009	**Research assistant at the Institut für Entwicklung und Frieden (INEF)/ Institute for Development and Peace, Duisburg**
April – July 2009; February – April 2008	**Intern at the Economic and Structural Reform Programme of the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) in Beijing, China**
June 2008 – January 2009	**Research assistant to Managing Director of the Institute of East Asian Studies (IN-EAST), Duisburg, Germany**
October 2006 – August 2007	**Student assistant at the Institute of Geography, University of Osnabrück, Germany**
July – August 2006	**Intern at the GIGA Institute of Asian Studies (IAS), Hamburg, Germany**
February – March 2006	**Intern at the Deutsche Stiftung Friedensforschung/German Foundation for Peace Research, Osnabrück, Germany**

Publications

- Zelli, F., Erler, D., Frank, S., Hein, J., Hotz, H., Santa Cruz Melgarejo, A.-M., 2014. Reducing emissions from deforestation and forest degradation (REDD) in Peru: a challenge to social inclusion and multi-level governance. Deutsches Institut für Entwicklungspolitik, Studies 85.
- Düspohl, M., Frank, S., Döll P., 2012. A review of Bayesian Networks as a Participatory Modeling Approach in Support of Sustainable Environmental Management. Journal of Sustainable Development 5 (12), 1-18.
- Erler, D., Frank, S., Hein, J.-I., Hotz, H.; Santa Cruz Melgarejo, A.-M.; Zelli, F., 2011. Inclusión social en el proceso REDD en el Perú: Una perspectiva de gobernanza en múltiples niveles. Deutsches Institut für Entwicklungspolitik (DIE)/Gesellschaft für Internationale Zusammenarbeit (GIZ), Proyecto Conservación de Bosques Comunitarios, Nota Técnica, No. 2.
- Frank, S., 2006. Project Mahathir: 'Extraordinary' Population Growth in Sabah. Südostasien aktuell - Journal of Current Southeast Asian Affairs 15 (5), 71-80.

Poster and Conference Proceedings

- Frank, S.K., Döll, P., Welp, M., Halik, Ü., Yimit, H., 2014. Assessing environmental trade-offs with Bayesian Decision Networks – Comparing ecosystem services and irrigation needs of urban and peri-urban plant species in Xinjiang, NW China. In: Ames, D.P., Quinn, N.W.T., Rizzoli, A.E. (Eds.): International Environmental Modelling and Software Society (iEMSs) 2014 - 7th International Congress on Environmental Modelling and Software, San Diego, California, USA, 16-19 June 2014.
- Frank, S.K., Pollino, C.A., Döll, P., 2014. Using Bayesian Networks to link Environmental Flows to Ecosystem Services in the Murray-Darling Basin, Australia. In: Ames, D.P., Quinn, N.W.T., Rizzoli, A.E. (Eds.): International Environmental Modelling and Software Society (iEMSs) 2014 - 7th International Congress on Environmental Modelling and Software, San Diego, California, USA, 16-19 June 2014.
- Frank, S., Döll, P., Welp, M., Halik, Ü., Yimit, H., 2013. Integrating experts' knowledge into Bayesian Networks – The case of ecosystem services of urban and peri-urban vegetation in Xinjiang, NW China, 5th Annual Conference of the Australasian Bayesian Network Modelling Society, Hobart, Australia, 27-28 November 2013.
- Frank, S., Döll, P., Welp, M., Halik, Ü., Yimit, H., 2013. Bayesian networks as tool for transdisciplinary knowledge integration – The case of dust weather and urban heat management in Xinjiang, NW China. Status Conference 2013 of the BMBF Funding Measure "Sustainable Land Management", Berlin, Germany, 17-19 April 2013.
- Düspohl, M., Frank, S., Siew, T.F., Döll, P., 2012. Transdisciplinary research for supporting environmental management. In: R. Seppelt, A.A. Voinov, S. Lange, D. Bankamp (Eds.): International Environmental Modelling and Software Society (iEMSs) 2012 - International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting, Leipzig, Germany, 01-05 July 2012.
- Frank, S., Döll, P., 2012. Poster "Application of Bayesian Networks for dust weather and urban heat management in the city of Aksu, Xinjiang, P.R. China" at the Annual Meeting of the Working Group "Desert Margin Research" of the German Society for Geography, Rauischholzhausen, Germany, 03-04 February 2012.