International Environmental Modelling and Software Society (iEMSs)
7th Intl. Congress on Env. Modelling and Software, San Diego, CA, USA,
Daniel P. Ames, Nigel W.T. Quinn and Andrea E. Rizzoli (Eds.)
http://www.iemss.org/society/index.php/iemss-2014-proceedings

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

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Abstract: Decisions in environmental management often have trade-offs attached: Either cost-benefit trade-offs, such as real costs and effectiveness of water treatment alternatives, or environmental trade-offs, such as environmental costs and benefits of land use alternatives which are more difficult to quantify. Vegetation managers in oasis towns of the Taklamakan desert in Xinjiang, NW China, were interested in a specific local environmental trade-off. They wanted to know which urban and peri-urban plant species were most effective in mitigating dust weather while needing the least irrigation. To assess this trade-off, we developed a Bayesian Network and two simple Bayesian Decision Networks (BDNs). BDNs use so-called decision and utility nodes to compare and rank management options according to their costs and benefits. In our research project, the BDNs perform a cost-benefit analysis by calculating the net benefits of 16 urban and peri-urban plant species according to their irrigation needs (= costs) and ecosystem services (= benefits). Our case study shows that BDNs can be easily adapted to specific needs of environmental planners and managers.

***Keywords**: Bayesian Decision Networks; trade-offs; ecosystem services*

1 INTRODUCTION

Bayesian Networks (BNs) are modeling tools which can be used to support decision-making under uncertainty (Molina et al. 2011, Varis et al. 2011, Carmona et al. 2013). In BNs, relations between variables are shown with directed links and quantified with the help of conditional probability tables (CPTs). These CPTs can be derived from a wide range of possible input data, including expert knowledge. The causal network structure helps to visualize complex problem fields as well as trade-offs between land and water uses (Baran et al. 2006, Carmona et al. 2011) or ecosystem services (Grêt-Regamey et al. 2013).

Although Bayesian Decision Networks (BDNs) can integrate costs and benefits of management measures explicitly, there are only few BDN applications to environmental and natural resource management in the literature. Ames et al. (2005) used a BDN to compare watershed management options according to their costs and their potential to decrease phosphorus loads. Sadoddin et al. (2005) developed a BDN on impacts of salinity management decisions on terrestrial and riparian ecology. Zhu and McBean (2007) conducted BDN analyses to compare water processing alternatives according to their costs and their water quality impacts as well as public health benefits. Barton et al. (2008) evaluated costs and benefits of eutrophication mitigation measures. Most of these BDN applications evaluate the monetary costs of management decisions in relation to their benefits. In our study, we analyzed irrigation needs of urban and peri-urban plants (= costs) in relation to the ecosystem services they provide (= benefits). Planting and maintaining vegetation also have monetary costs attached. However, as water scarcity is the limiting factor in oasis towns of the Taklamakan desert, we solely focused on irrigation needs.

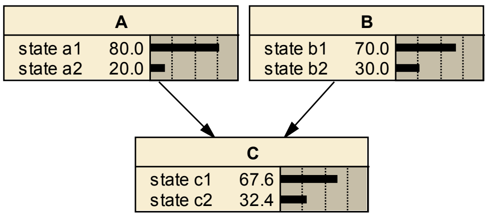
In contrast to other BDN applications, our BDNs were not developed as independent models but serve as add-ons to an already existing Bayesian Network. Together with local experts, we first developed a BN on ecosystem services and irrigation needs of urban and peri-urban vegetation in the oasis towns Aksu and Korla. Whereas BNs can be used to evaluate the impact of management decisions on all variables in the network, BDNs solely provide rankings of management decisions. As finding an optimal combination of management decisions with a BN takes a lot of time, we decided to develop two BDNs in addition to our expert-based BN. The BDNs provide rankings from most suitable plant species to least suitable plants species. These rankings are interesting for local vegetation managers and could also make it easier for them to use our BN.

In this paper, we present how we used BNs and BDNs to meet the demands of local vegetation managers in oasis towns of the Taklamakan desert. We suggest combining these two modeling tools more often and conclude that BDNs can be very useful to analyze environmental trade-offs with non-monetary costs. In section 2, we provide an introduction into BN and BDN modeling. In section 3, we present our expert-based BN and BDNs on ecosystem services and irrigation needs of urban and peri-urban plants. In section 4, we present results from our BDNs. In section 5, we draw some conclusions.

2 BAYESIAN NETWORKS AND BAYESIAN DECISION NETWORKS

2.1 Bayesian Networks

All BNs in this paper were generated using Netica™ Version 4.6 (Norsys, http://www.norsys.com). The software depicts variables in light-colored rectangles which are called nature nodes. The directed links between the nodes indicate causal relations. In Figure 1, the parent nodes A and B influence their child node C. The strength of this influence is expressed in conditional propability tables (CPTs). Each row in a CPT can be read as “if-then-sentence”. Nodes without parent nodes are called root nodes; nodes without child nodes are called leaf nodes. For root nodes unconditional probability tables can be used to represent observations, scenarios, management options as well as spatial distributions (Bromley 2005, Smith et al. 2007).



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 1: On the left, BN with three nodes (A, B, C) and two states each (a1/a2, b1/b2, c1/c2); on the right, the CPT of node C.

To calculate the probability distributions of the child node C, the BN software needs its conditional probability table P (C|A,B) and the unconditional probabilities of the parent nodes P(A) and P(B). First, the BN software uses the fundamental rule of probability to calculate the joint probability P(A,B,C). Then the software marginalizes the probabilities of each state of P(C) out of the joint probabilities P(A,B,C) and adds them together (Table 1) (Jensen and Nielsen 2007).

Table 1: Joint probability calculation and marginalization of P(C) out of P(A,B,C).

	a1		a2		
	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 %)

BNs use the Bayes' rule (1) to recalculate probability distributions after new information is entered in one or more child nodes. This is called belief updating and provides the possibility to iteratively improve BNs whenever new data or knowledge exists.

$$(1)\ \mathrm{P(A|B)} = \frac{\mathrm{P(B\mid A)*P(A)}}{\mathrm{P(B)}}$$

2.2 Bayesian Decision Networks

Bayesian Decision Networks (BDNs) are BNs with so-called decision nodes and utility nodes. In Netica, decision nodes are depicted as blue-colored rectangles; utility nodes are depicted as red-colored diamonds (Figure 2). Costs are expressed in values between -1 and 0; benefits are expressed in values between 0 and 1.

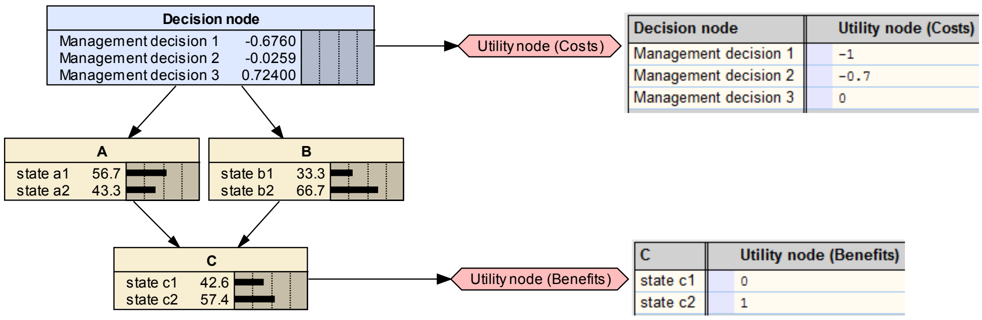


Figure 2: BDN with three nature nodes (A, B, C), one decision node, and two utility nodes for costs and benefits with their tables.

In our example BDN, the software calculates the total expected utility (EU) for each management decision(2) (adapted from Jensen and Nielsen 2007):

$$(2)\ \mathrm{EU\ (Mgmt\ 1) = Costs\ (Mgmt\ 1)} + \textstyle\sum_{C} \mathrm{Utility(C) * Probability\ (C|Mgmt\ 1)}.$$

The values shown behind each management decision can range between -1 and 1. Negative values indicate that costs outweigh the benefits; positive values indicate that benefits outweigh the costs. The management decision with the highest value, here Management decision 3, has the highest net benefit. As the software does not rearrange the states of the decision node according to their total expected utilities, we suggest visualizing the BDN results with additional figures.

3 CASE STUDY: ECOSYSTEM SERVICES AND IRRIGATION NEEDS OF URBAN AND PERI-URBAN PLANTS IN XINJIANG, NW CHINA

Urban and peri-urban vegetation provides many ecosystem services for people living at the margin of the Taklamakan desert (Halik 2003). As oasis towns, 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 important ecosystem services in the region. The term dust weather describes dust events in which desert dust particles are raised and transported by the wind. To mitigate dust weather and to control desertification in China, the Three Norths Forest Shelterbelt program has been carried out since the late 1970s. There is a controversial debate to what extent these afforestation programs have been successful. The replacement of natural vegetation by artificial shelterbelts as well as the low survival rate of newly planted trees caused skepticism among some researchers (Wang et al. 2010). Our BN analyzes the impact of 11 peri-urban plants on dust weather mitigation. Some of these plants, e.g. *Tamarix ramosissima Ledeb.*, belong to the natural vegetation on dunes which protect the soil from wind-soil erosion. Other plants, such as *Populus alba L.*, are used for shelterbelts which serve as wind breaks and dust filter.

Although local vegetation managers were mainly interested in dust mitigation through peri-urban vegetation, we also included the provision of shade by urban vegetation in our BN. 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 Taklimakan desert would even experience higher temperatures. Therefore, our BN compares 10 urban plant species in their ability to provide shade. Due to limited water resources in the case study region, the BN also highlights the irrigation needs of plant species and varying vegetation covers.

3.1 Bayesian Network

We developed the BN together with local experts. In 2011, we conducted expert interviews to jointly define the model purpose. In 2012-2014, we conducted three expert workshops in Urumqi and Korla (1) to discuss the network structure, (2) to elicit experts' estimates for the parameterization of the BN, and (3) to present and to discuss the final BN model. The final BN consists of 16 nodes. Six of the CPTs (▲) were derived from the estimates of three expert groups. The expert groups could give their estimates on the ability of each plant species to protect the soil from wind-soil erosion, to serve as wind break, to filter dust, and to provide shade. These estimates were elicited in values between – and +++. The estimates on irrigation needs of each plant species were elicited in estimates between 0-1. In addition to these estimates, the expert groups were asked how confident they were in their estimates. As the estimates from the three expert groups were very similar, we calculated the combined weighted average of all experts' estimates. These combined estimates were systematically converted into CPTs with the help of conversion tables. These conversion tables assigned probability distributions to certain classes, e.g. for values which can range between 0-1, values between 0-0.1 have the greatest fraction of 100% in the class "very low". Six CPTs (●) were calculated by using equations that equally weighted the incoming parent nodes. There was a lack of consensus among the experts regarding the question which of the parent nodes of "Plant-specific dust weather mitigation" was more influential than the others. Therefore we decided to equally weight the parent nodes to provide an unbiased version.

The green-colored nodes represent the (regulating) ecosystem services regarding the mitigation of dust weather and the provision of shade. These ecosystem services depend on plant species and the size of urban and peri-urban vegetation cover. The yellow-colored nodes show the irrigation needs of plants and urban and peri-urban vegetation. The blue-colored nodes are root nodes which can be used to analyze their impact on the leaf nodes.

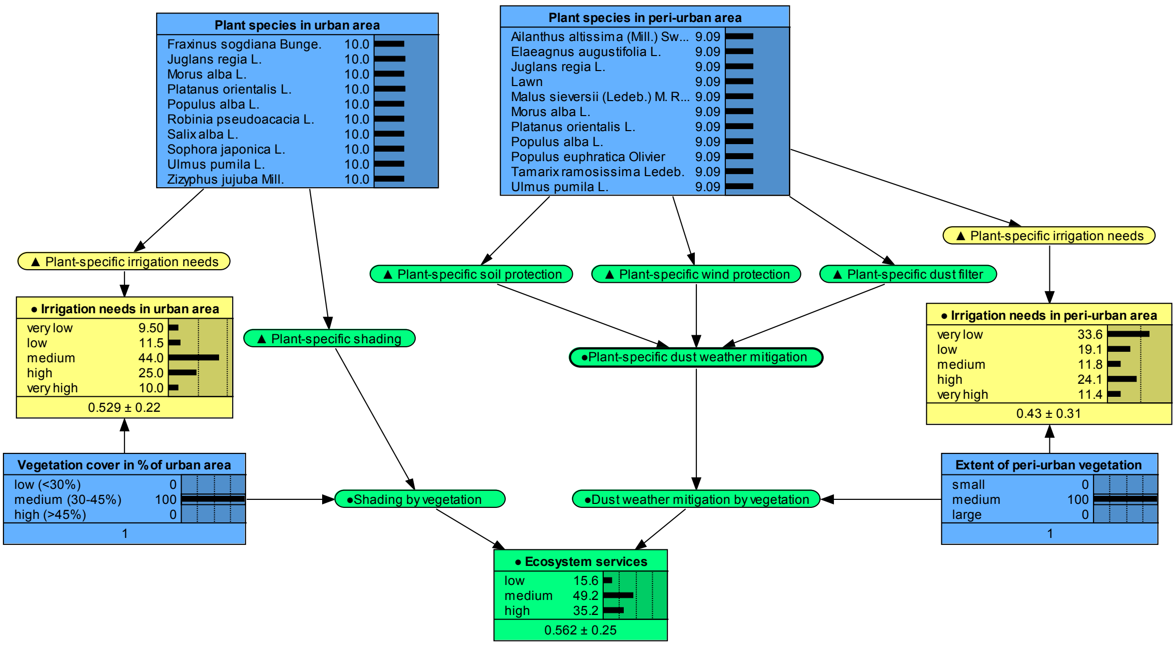


Figure 3: Final BN on ecosystem services and irrigation needs of 16 urban and peri-urban plant species.

In our BN, the root nodes can be used, to evaluate the impact of single plant species or combinations of plant species and the impact of vegetation cover on "Ecosystem services", "Irrigation needs of urban vegetation", and "Irrigation needs of peri-urban vegetation". In this BN, setting the probability of a single plant species to 100% would be interpreted as planting only this one plant species in the whole urban or peri-urban area. As this is neither realistic nor desirable, the 100% should be distributed among several plant species to identify the most suitable combination of plant species. This is a very difficult task, if root nodes have more than 10 states. Therefore, we developed two simple BDNs to receive a ranking of our plant species (Figure 4 and 5). The rankings can help the model user to find a combination of urban and peri-urban plant species that effectively mitigates dust weather, increases shading and reduces the amount of water needed for irrigation.

3.2 Bayesian Decision Networks

The BDN on plant-specific dust weather mitigation consists of one decision node with 11 states, two utility nodes for irrigation needs (= costs) and plant-specific dust weather mitigation (= benefits).The BDN on plant-specific shading consists of one decision node with 10 states, two utility nodes for irrigation needs (= costs) and plant-specific shading (= benefits) (Figure 4 and 5).

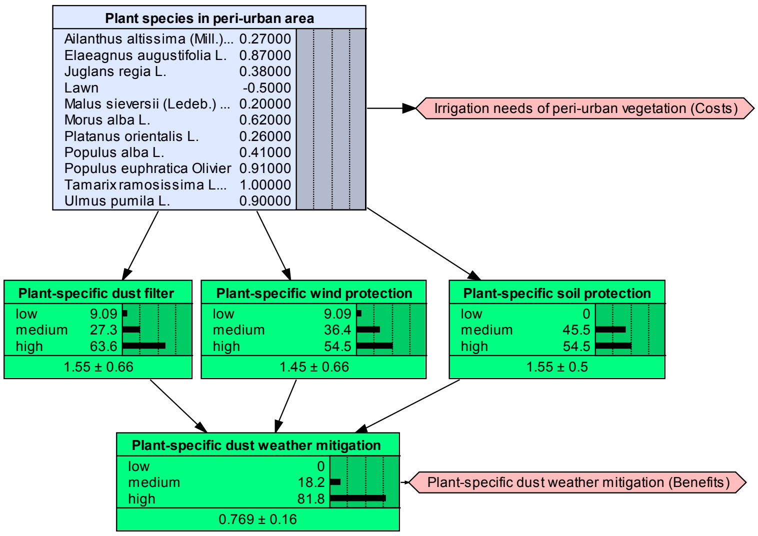


Figure 4: BDN on plant-specific dust weather mitigation.

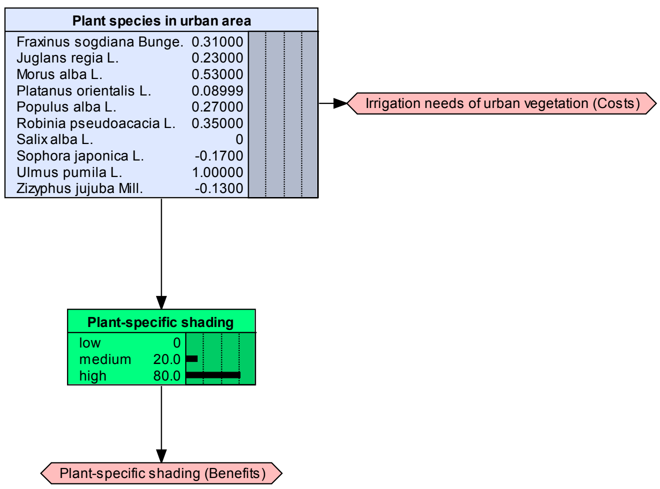


Figure 5: BDN on plant-specific shading.

The BDNs were developed on the same basis of expert estimates as our BN. The only difference is that we calibrated the model in a way that the most effective peri-urban plant species could reach the "high" plant-specific dust weather mitigation and the most effective urban plant species could reach the “high” plant-specific shading. This way, we ensured that the highest benefits (+1) were put on a par with the highest costs (-1).

4 RESULTS

The total expected utilities of plants species, shown in the decision nodes, provide the possibility to analyze the irrigation needs of urban and peri-urban plants in relation to their ecosystem services. For peri-urban plants, the total expected utilities range from -0.5 for lawn to +1 for *Tamarix ramosissima Ledeb*. For urban plant species, the total expected utilities range from -0.17 for *Sophora japonica L.* to +1 for *Ulmus pumila L.* (Figure 5).

Lawn has the highest irrigation need and is therefore not wide-spread in peri-urban areas. However, due to its aesthetic value, lawn is planted in urban areas and along some parts of major highways in the case study region. The results indicate that natural vegetation on dunes, such as *Tamarix ramosissima Ledeb.*, is most effective in mitigating dust weather while needing the least irrigation. The ranking of plant species therefore raises the question of how peri-urban vegetation, especially shelterbelts, should be planned in an optimal way.

The fact that most plants are very effective in mitigating dust weather (green columns in Figure 6) can be explained by the way how the plant species were chosen. A scientific domain expert intentionally chose plants which are already planted in Aksu and Korla as well as plants which are very effective in his opinion and should be planted more often. Apparently all three expert groups who evaluated the plants shared his opinion, that these 16 plants were very suitable for dust weather mitigation. The irrigations needs (red columns) vary more strongly between plants species. The total expected utility (black graph) can be used to rank the plants according to their net benefits.

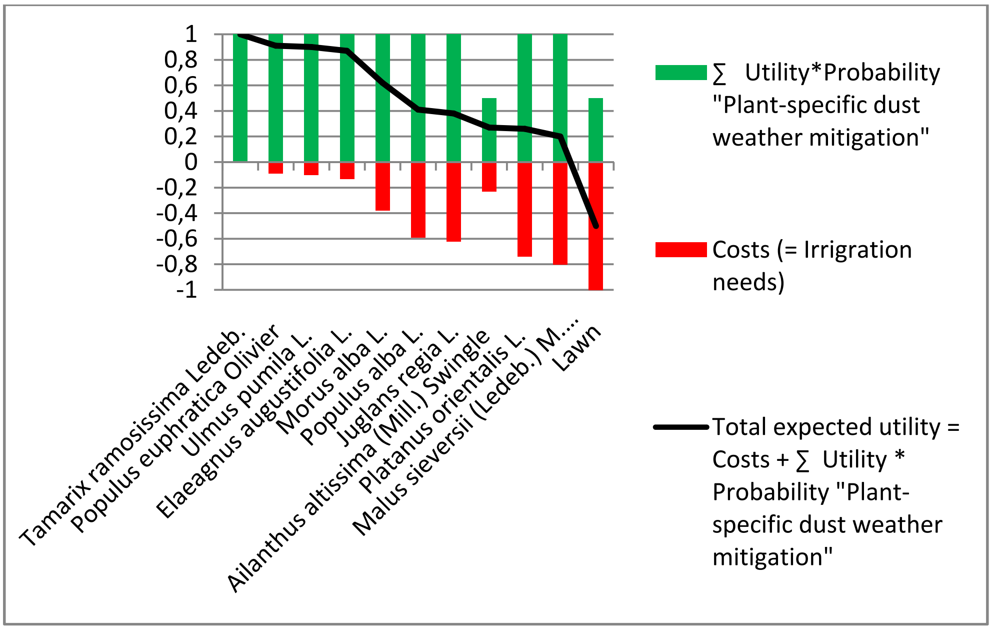


Figure 6: Total expected utility of peri-urban plant species based on their irrigation needs and their ability to mitigate dust weather.

5 CONCLUSION

Due to limited access to data, we developed our BN and BDNs on the basis of expert knowledge only. Our BN and BDNs visualize how local experts from forestry science and urban vegetation management evaluate the potential of urban and peri-urban plants to mitigate dust weather and to provide shade. It would be interesting to add provisioning services in our BN as some of the plant species provide fruits, e.g. apples and walnuts. Then the BN could visualize the trade-off between different types of ecosystem services while putting an emphasis on the irrigation needed to provide these services.

Our case study shows that BDNs are suitable to assess environmental trade-offs even if the costs are non-monetary. The cost-benefit analysis reveals net benefits of all management decisions, in our case of urban and peri-urban plant species, which are relevant for environmental planners and managers. On the last expert workshop in March 2014, the workshop participants tested and evaluated our BN and BDNs. The rankings from our BDNs clearly made it easier for them to use our BN on ecosystem services and irrigation needs.

ACKNOWLEDGMENTS

This research project was carried out within the SuMaRiO project funded by the German Federal Ministry of Education and Research (BMBF).

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