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Modelling with stakeholders: a systems approach for improved environmental decision making under great uncertainty

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Abstract: In this paper an integrated participatory modelling approach is introduced for managing complex water resource systems under great uncertainty due to climatic and non-climatic factors. A number of case studies are provided to demonstrate the effectiveness of the methodology. The approach includes a range of stakeholders' engagement activities throughout the modelling process. The first step consists of participatory problem scoping and model conceptualisation, where the modellers work closely with the stakeholders to establish the scope of the work, identify the key variables, determine the system boundaries, and develop an initial conceptual model. Secondly, a structural analysis technique is used to understand the interactions between the systems variables. Next, the conceptual model is transformed within either a Bayesian Network (BN) and/or Systems Dynamics (SD) model. BNs can deal with uncertainty, missing and interdisciplinary data by integrating experts' opinions and process-based models outputs, while SDs allow for temporal analyses, including feedback loops. Because of the complementary perspectives they offer, we also propose a method to integrate the two models in this paper to develop a more robust decision support tool. Experts and stakeholders are also involved during the BN/SD model development through data elicitation, and at the end of the modelling exercise for final model revision and testing. The final product is a participatory, multidisciplinary decision support system (DSS), deployed by the same stakeholders who helped develop it, which allows for a robust water resources management decision-making under uncertain conditions.

***Keywords**:* Participatory modelling; Uncertainty; Climate change; Bayesian Networks; Systems Dynamics

1 INTRODUCTION

Decision support systems (DSS) have been developed for assisting water managers throughout the past decades (e.g. Soncini-Sessa, 2003; Argent et al., 2009; Stewart and Purucker, 2011; Bertone et al., 2015a). DSS can be created for quasi real-time management or for long-term strategic planning (Matthies et al., 2007). However, in a large number of cases, the system is modelled deterministically and the uncertainty is either overlooked or only partially considered. In addition, stakeholders, who are often contextualised as DSS end-users, are often neglected in the engagement strategy (Soncini-Sessa, 2003). The relative paucity of DSS being implemented is due to the lack of transparency for the end-users (Van Delden, 2011) and a lack of trust in effective, but often complex, algorithms (Rizzoli and Young, 1997). Another challenge is that the management of water resources involves the considerations of several different systems (e.g. hydrodynamics, land-use, weather, economy, health), which have rarely been integrated within the same model. Moreover, predicted changes in climate would dramatically increase the uncertainty and difficulty in modelling, predicting and optimising water resources. Based on these factors, four objectives have been identified for developing a meaningful DSS; (1) identify and engage the key stakeholders in developing the DSS (accessibility and participation); (2) incorporate all areas of expertise to obtain a comprehensive model (integration); (3)

devise a robust modelling methodology to deal efficiently with uncertainties and missing data; and (4) address the role of feedback loops and system structure in driving system behaviour over time (dynamic).

A number of probabilistic approaches for developing environmental DSS have been used in past studies to address uncertainty and integration (e.g. Reichert et al., 2007; Dorner et al., 2007). Studies have also previously integrated expert opinion into the development of their DSS (e.g. Nicholls and Holecek, 2008; Tompkins et al., 2008) or, more broadly, used participatory modelling (e.g. Richards et al., 2013; Kersten, 2015). In fact, since 2007 there has been a tendency towards stakeholder participation in the development of DSS and the decision-making process (Matthies et al., 2007). However, a clear modelling framework integrating the four main objectives listed above is not evident. Also, there do not appear to be any studies integrating stakeholder engagement, Bayesian Networks (BN) and Systems Dynamics (SD) modelling under a same methodology framework. In this paper, we present a comprehensive, integrated participatory modelling approach along with a case-study demonstrating its effectiveness.

2 MATERIALS AND METHODS

2.1 The Accessible, Robust, Integrated and Dynamic (ARID) DSS approach

Figure 1 illustrates the proposed ARID approach. As shown in the figure, the involvement of the stakeholders is essential throughout the modelling exercise. The proposed methodology offers an Accessible, Robust, Integrated and Dynamic DSS framework that provides a more logical and integrative approach to problem solving and is consistent with addressing the social-economical-environmental dimensions of water management. This would result in a user-friendly (accessible), yet scientifically rigorous (robust) tool that puts together (integrative) multi- and trans-disciplinary knowledge/data, including the expert opinion of stakeholders, based not only on the probabilistic Bayesian approach, but also system dynamics approach (dynamic).

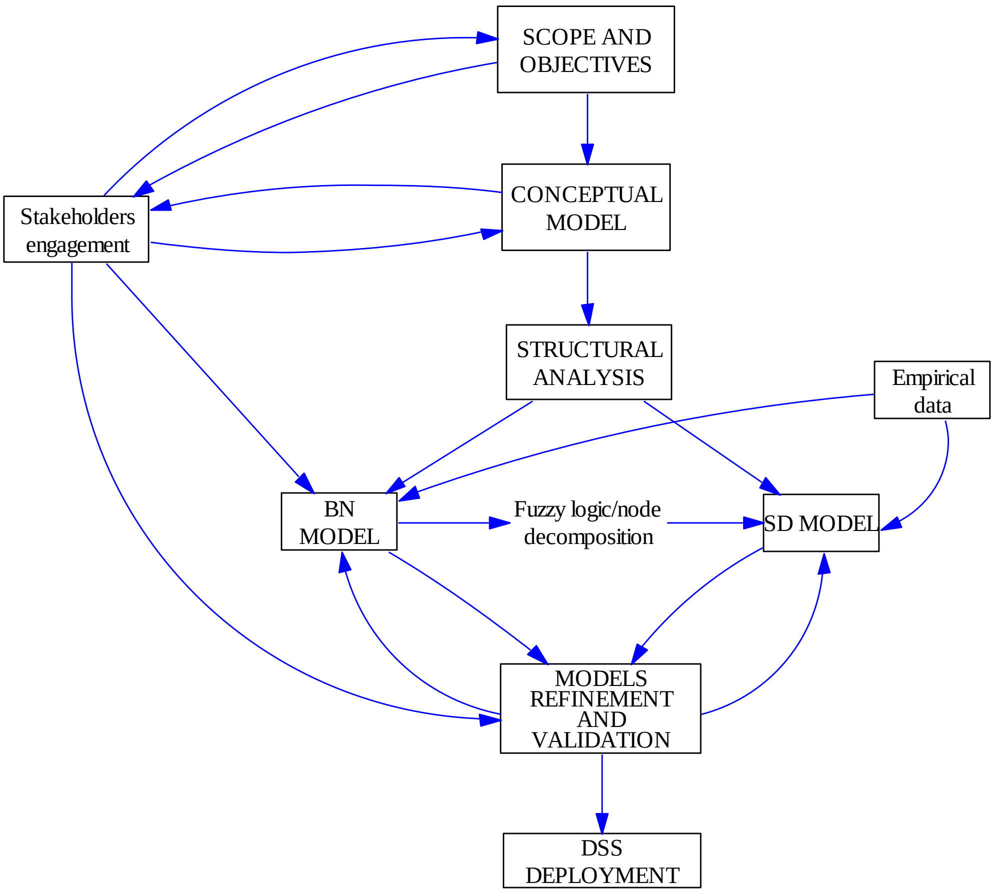

Figure 1 Conceptual ARID framework

2.2 Conceptual model development and structural analysis

A number of mechanisms ensure the project in hand would be contributing in a coordinated way to addressing the overall research problem. The first mechanism involves clarifying the set of research questions/objectives together with stakeholders at a scoping workshop. The second mechanism involves developing a shared conceptual model of the system. This conceptual model will serve a number of purposes, including (1) establishing a common project framework and lexicon for communication between the various project components/participants, (2) identifying the most important system components, chains of causal relationships and feedbacks, and (3) providing the basis for more formal modelling using a Bayesian Belief Network (BBN) approach plus system dynamics simulation.

The first step in developing a conceptual model is to agree upon the focal variable/s among the stakeholders. Researchers typically take a somewhat informal and haphazard approach to formulating conceptual models of systems. The problem with doing this is there is a tendency to focus on variables and connections that are most familiar to the researchers' domain of expertise. However, there are tools that can facilitate a more rigorous approach to the model conceptualisation process such as the Cross-Impact Matrix Multiplication Method (CIMMM) (Godet, 2001).

As Godet stated, structural analysis allows describing the system by linking up constituent elements of a system through a matrix. The method has the advantage of stimulating reflection within the group, and directing participants it to think about certain aspects, which are sometimes counterintuitive. The method consists of three stages. The first involves problem identification where the current state is described comprehensively. The second involves the identification of candidate variables and likely interactions between these variables and, finally, in the third stage, structural analysis is used to identify key variables.

2.3 Coupling BN-SD modelling approaches

The next step is to transform the coalesced conceptual model into a BN and/or SD model. BN and SD have mutual, complementary benefits and limitations, and thus, a technique to integrate BN with SD is also proposed to maximise their respective advantages. Both BD and SD can facilitate stakeholder engagement throughout the entire modelling process (e.g. using expert elicitation to draw data from the knowledge base).

Bayesian Network (BN) modeling is a probabilistic-based methodology structured on Bayes theorem (Fenton and Neil, 2008). The structure of any given BN consists of a set of variables (also called nodes) that are connected by arcs to reflect direct relationships (note that the arcs can be characterised to show inductive and/or deductive reasoning in a BN). The causal relationships between directly connected nodes are quantified through Conditional Probability Tables (CPTs). Populating the CPTs is one of the most challenging parts of developing a BN, but at the same time one of its most important (alongside model structure development) and powerful features that distinguishes it from the softer decision support systems tools (Henriksen et al., 2007), especially in a context where stakeholder inputs are essential. Additional advantages of BN are (Uusitalo, 2007): (1) effective data management - ability to deal with missing (latent variables) and sparse data; integrating trans- and multi-disciplinary variables within the same model (e.g. social and ecological variables); integrating different types of data (e.g. empirical, expert judgment, other model outputs); (2) simulations are fast facilitating rapid feedback to participants when testing different scenarios, which, in turn, supports effective decision-making; and (3) the ability to detect and explore inconsistencies and different perceptions among stakeholders; understanding these inconsistencies and misperceptions can represent one of the solutions for improved management (Hukkinen, 1993). However, there are several key constraints to using BNs. Temporal analyses are difficult and can lead to unwieldy model structures. Furthermore, feedback pathways are not supported in the structure of BNs (i.e. DAGS (directed acyclic graphs) are used), restricting them to static analysis. Finally, discrete variables are typically favoured over continuous variables (especially for BNs parameterised by expert opinion), with discretisation often limited to only a few states per variable (e.g. Richards et al., 2013). This results in a coarsely-parameterised model thus reducing its performance and utility (Uusitalo, 2007).

System dynamics (SD) modelling represents an approach for understanding the structure and dynamics of complex systems, as well as facilitating the development of formal computer simulations of such systems, which are then used to design improved policies and decision-making (Sterman, 2000). SD is complementary to BN due to its ability to include time as a variable (as well as feedback loops), thus, coupling these two methods eliminates their weaknesses while providing a more robust technique for addressing complex issues.

In addition to coupling BN and SD modelling, it is possible to apply an integrative, fuzzy logic approach in which the structure of the BN, as well as CPTs of certain nodes, is used to numerically describe and quantify uncertain variables. The value of integrating fuzzy logic and the creation of "fuzzy system dynamics" was highlighted by Tessem and Davidsen (1994). Such use of fuzzy logic to represent vagueness and uncertainty in systems characteristics has also been used in water resource optimisation studies (Labadie 2004) and within a coupled fuzzy logic – systems dynamics approach by Khanzadi et al. (2011).

This "fuzzy logic" – based approach can be used to quantify relationships and values for a number of nodes wherever empirical evidence is not available. The integration of fuzzy logic into the SD structure can be performed in a way that the values of different variables are determined by fuzzy numbers based on the outputs of BN. For instance, it is likely to have a node for which empirical data are not available, but whose relationships with some other variables were quantified by the stakeholders in the BN. The BN node can then be decomposed into its different states within the SD; assuming for instance two states "high" and "low", and two new variables will be created in the SD, i.e. "node's high value risk" and "node's low value risk". As these risks are quantified numerically in the associated CPT of the BN, functions (e.g. lookup) can be used to quantify these risks in the SD. Moreover, to account for random variability, a random number within a meaningful range can be added and several simulations (Monte-Carlo approach) can be run. Often, as a direct logical consequence of using probabilities (which have values included between 0 and 100%), these variables have to be normalised. However, denormalisation (or "defuzzification") can be applied for those nodes where the numerical values (i.e. "crisp outputs") are relevant, after calibrating the model with historic data and/or based on thresholds of concern. Experts' involvement in defuzzification is critical to yield sensible, crisp outputs.

An example is provided in Figure 2, where it is assumed that there are no empirical data available for rainfall. Nevertheless, stakeholders populated the associated CPTs in the BN. It is therefore possible to create a fuzzy variable "high inflow risk", whose value is based on the CPTs (importantly, all the numerical thresholds of the different states of the nodes must be defined). Again from the BN, it is possible to calculate the high turbidity risk from the CPTs (which were estimated based on empirical data in this case) by building an appropriate function (e.g. through regression analysis). We now have a time-series for high turbidity risk. By having historical data, it is possible to defuzzify this variable by proper calibration (e.g. assuming that the highest risk corresponds to the highest historical value recorded).

The proposed fuzzy logic approach with BN node decomposition is an effective way to complete and deploy a SD model whenever several variables do not have empirical data available. However, if most of the data are not available, SD is not the best modelling approach and it is recommended to develop the BN only.

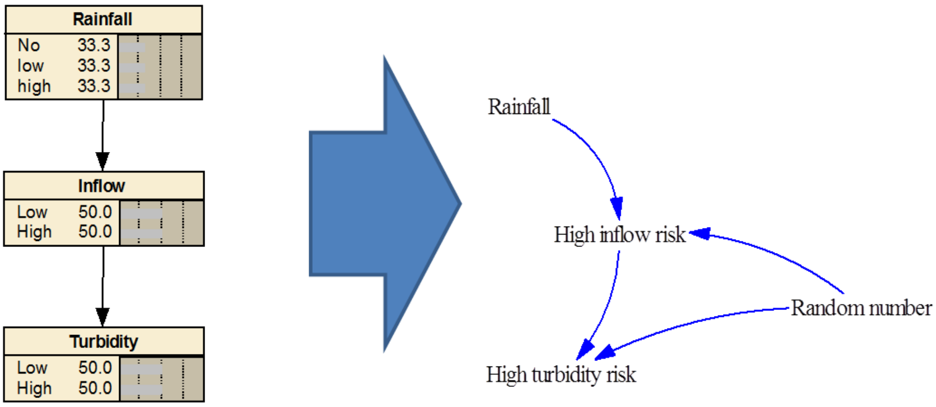

Figure 2 Example of BN node decomposition for SD modelling

2.4 DSS refinement, testing and deployment

After the BN and SD models have been built, it is important to obtain feedback from the stakeholders to try to refine the structure before eliciting data. This activity increases stakeholder engagement and results in fewer misunderstandings during the data elicitation phase. Subsequently, after the data are entered and the models refined, these can be tested over historical events or with a number of different techniques (e.g. as discussed in Fenton and Neil, 2012).

Eventually, the final participatory DSS can be implemented by the stakeholders themselves with the support of the researchers. Empowering stakeholders in this way not only facilitates the identification of the most important parameters and a greater understanding of the system being modelled (Vennix, 1996), but it also increases the likelihood of the final developed decision support tool being accepted and used, thus overcoming the limited deployment issues raised in Rizzoli and Young (1997) and van Delden (2011).

3 RESULTS

In this section we describe the methodology and results of a completed project, prior to illustrating the methodology for a new larger and multidisciplinary project underway.

3.1 Modelling the impact of extreme events on reservoir's health-related water quality

The goal of this project was to rank extreme events, which will be exacerbated by climate change, based on the risks they pose to health-related reservoir water quality and the ability of the treatment plant to deliver safe drinking water. The project was conducted in a large Australian reservoir supplying a densely populated metropolitan area. Stakeholders (e.g. water utility managers, scientists, operators) were engaged and a number of workshops were run to identify the critical variables to be modelled, the spatial/temporal boundaries, and to conceptualise the initial model. This was transformed in a highly interdisciplinary BN, with nodes of different types such as environmental, water quality, land use, policy-making, management options, and weather (see Bertone et al., 2015b). Only a limited amount of empirical data was available, thus elicitation of data from experts was a critical step for this project. After the BN was built and filled with empirical/soft data, a SD was developed based on a similar structure of the BN. However, the SD was deprived of nodes with no empirical data available and with a minimum influence on the target variables (based on the BN sensitivity analysis), while the few remaining variables with no empirical data but large influence on the overall system, were modelled using the proposed fuzzy-logic/BN node decomposition approach explained above.

In conclusion, the BN allowed extreme events to be ranked based on the final risk of poor water quality; interestingly, it was also possible to discern how quite different results were obtained according to the stakeholder's expertise used to derive the BN model. On the other hand, with the SD model, it was possible to detect nonlinear responses of the system: for instance, an increase in annual rainfall of 15% would pose a greater risk than an increase of 30%, as this would lead to a much lower risk of bushfires. Moreover, other factors such as population growth and increased water demand could be modelled. However, the use of BN outputs for modelling certain influential nodes with no empirical data (i.e. BN node decomposition) was essential for the development of the SD.

3.2 Next generation ARID

Over the long term, the proposed methodology is going to be tested further and refined. Importantly, for instance, further innovations to the methodology are proposed, such as the use of smart technology, such as software applications (Richards et al., 2014) or virtual reality tools, to facilitate data elicitation. This next generation ARID modelling approach will be applied and further improved in an ongoing five-year project, where a number of climate change adaptation options will be modelled for different islands in the Pacific Region. Separate research groups will investigate the cost-benefits of these options from different angles: a number of models will be built, such as coastal, socio-economic, and public health models. Firstly, a number of workshops, with both modellers and local communities, will be run to gain a comprehensive understanding of the systems, identifying targets and possible solutions. The system will be then conceptualised and BN/SD models built. At the end of the project, these models will be populated with: (1) available empirical data, (2) expert/local community knowledge, and (3) the results of the specific models developed by the different research groups as mentioned above. The ability, especially of BN, to integrate different types of data is a key for the development of the final DSS for this project. The parallel development of a SD model will also give insights on the dynamic responses of islands to changes in climate and investments in adaptation. The successful integration of socio-economic, biophysical and health-related model outputs will provide further evidence of the versatility of the proposed ARID methodology framework, and its adaptability and applicability to both small and large problems from a wide range of different disciplines.

4 CONCLUSIONS

An integrated participatory modelling approach for the development of participatory decision support systems to manage complex water resources management under multifaceted uncertainty (i.e. climate and non-climate factors) has been presented. The approach relies on constant stakeholders' engagement in all the main phases of the DSS development. This leads to: (1) an increased, shared understanding of the conceptualised system; (2) an ability to deal with missing data and uncertain variables by eliciting experts' opinions; and (3) an enhanced credibility and deployment of the final DSS.

We also propose and integrated Bayesian Networks / Systems Dynamics modelling approach whenever appropriate. While SD cannot explicitly deal with uncertainty or missing data, the proposed fuzzy logic/ BN node decomposition approach allows for the use of BN outputs to overcome such limitation and thus combine the BN benefits with the ability of SD to consider time and feedback loops in the system.

A case study, describing a recently completed project, has been presented where the proposed methodology has been applied. Further, another case study is described, representing an ongoing project, where the proposed methodology is further refined by introducing smart technology and a more complex integration of outputs from separate models, experts' opinions and empirical data. These examples provide evidence of the effectiveness of the proposed methodological framework.

The proposed BN node decomposition approach is ideal when only a small percentage of the SD variables have no empirical data, since it would allow for the completion and deployment of the model; however, at this stage it is not recommended if several variables lack of empirical data, and a BN model only would be instead the most suitable option. More research is needed to further explore possibilities to integrate BN outputs, uncertainty and missing data into a comprehensive fuzzy, probabilistic systems dynamics modelling approach.

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REFERENCES

Argent, R.M., Perraud, J.-M., Rahman, J.M., Grayson, R.B., Podger, G.M., 2009. A new approach to water quality modelling and environmental decision support systems. Environ. Modell. Softw., 24, 809-818.

Bertone, E., Stewart, R.A., Zhang, H., Bartkow, M. and Hacker, C., 2015a. VPS-Based decision support system for manganese forecasting in subtropical water reservoirs. Environ. Modell. Softw. 73, 133-147

Bertone, E., Sahin, O., Richards, R., Roiko, R., 2015b. Bayesian Network and System Thinking modelling to manage water quality related health risks from extreme events. 21st International Congress on Modelling and Simulation (MODSIM), Gold Coast (Australia), December 2015.

Dorner, S., Shi, J., Swayne, D., 2007. Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model. Environ. Modell. Softw 22 (2), 211-222.

Fenton, N., and Neil, M., 2008. Risk assessment and decision analysis with Bayesian Networks. CRC Press, Taylor & Francis Group. Boca Raton, FL, USA.

Godet, M., 2001. Creating futures: scenario planning as a strategic management tool. Econ., London

Henriksen, H.J., Rasmussen, P., Brandt, G., von Bülow, D., and Jensen, F.V., 2007. Public participation modelling using Bayesian networks in management of groundwater contamination. Environ. Modell. Softw., 22, 1101-1113.

Hukkinen, J., 1993. Bayesian analysis of agricultural drainage problems in California's San Joaquin Valley. J. Environ. Manag., 37, 183-200.

Khanzadi, M., Nasirzadeh, F., Alipour, M., 2011. Integrating system dynamics and fuzzy logic modeling to determine concession period in BOT projects. Autom. Constr. 22 (2012) 368–376

Labadie, J.W., 2004. Optimal operation of multireservoir system: state-of-the-art review. J. Water Resour. Plan. Manag., 130(2), 93-111.

Matthies, M., Giupponi, C., Ostendorf, B., 2007. Environmental decision support systems: Current issues, methods and tools, Environ. Modell. Softw., 22(2), 123-127

Nicholls, S., Holecek, D.F, 2008. Engaging Tourism Stakeholders in the Development of Climate Change Decision-Support Tools: A Case Study from Michigan, USA. Tour. Rev. Intern. 12(1), 25-42(18)

Reichert, P., Borsuk, M., Hostmann, M., Schweizer, S., Spörri, C., Tockner, K., Truffer, B., 2007. Concepts of decision support for river rehabilitation. Environ. Modell. Softw 22 (2), 188-201

Richards R., Sano, M., Roiko, A., Carter, R.W., Bussey, M., Matthews, J., and Smith, T.F., 2013. Bayesian belief modeling of climate change impacts for informing regional adaptation options. Environ. Model. Softw., 44, 113-121

Richards, R.G., Sahin, O., Sano, M., Meynecke, J.-O., Tiller, R., 2014. App2Adapt: Using tablet technology to elicit conditional probabilities for Bayesian Belief Network Modelling. Proceedings of the 7th International Congress on Environmental Modelling and Software. Eds. D.P. Ames, N. Quinn. San Diego, California, USA

Rizzoli, A.E., Young, W.J., 1997. Delivering environmental decision support systems: software tools and techniques. Environ. Modell. Softw., 12 (2-3), 237-249.

Soncini-Sessa, R., Castelletti, A., Weber, E. 2003. A DSS for planning and managing water reservoir systems. Environ. Modell. Softw., 18, 395-404.

Sterman, J.D. 2000. Business dynamics: systems thinking and modeling for a complex world. The McGraw-Hill Companies; Printed in the United States of America.

Stewart, R.N., Purucker, S.T. 2011. An environmental decision support system for spatial assessment and selective remediation. Environ. Modell. Softw., 26, 751-760.

Tompkins, E., Few, R., Brown, K., 2008. Scenario-based stakeholder engagement: Incorporating stakeholders preferences into coastal planning for climate change, J. Environ. Manag., 88(4), 1580-1592.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Model., 203, 312-318.

Tessem, B., and Davidsen, P.I., 1994. Fuzzy system dynamics: an approach to vague and qualitative variables in simulation. Syst. Dyn. Rev., 10(1), 49-62.

van Delden, H., Seppelt, R., White, R., Jakeman, A.J., 2011. A methodology for the design and development of integrated models for policy support. Environ. Modell. Softw., 26, 266-279.

Vennix, J.A.M., 1996. Group Model Building. Wiley: Chichester.