To be cited as: Sušnik, J., J.-L. Molina, L.S. Vamvakeridou-Lyroudia, D.A. Savić and Z. Kapelan (2012) Comparative analysis of System Dynamics and Object-Oriented Bayesian Networks modelling for water systems management. Water Resources Management, Vol 27, No 3, pp. 819-841.

Comparative analysis of System Dynamics and Object-Oriented Bayesian Networks modelling approaches for aquifer systems management: application to the Kairouan aquifer (Tunisia)

Janez Sušnik[a,*], Jose-Luis Molina[b], Lydia S. Vamvakeridou-Lyroudia[a], Dragan A. Savić[a], Zoran Kapelan[a]

[a,*] Corresponding author. Centre for Water Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, Devon, UK, EX4 4QF. Email: j.susnik@exeter.ac.uk. Tel: +44 (0) 1392 723730

[b] High Polytechnic School of Engineering Ávila. Area of Hydraulic Engineering, Salamanca University. Av. de los Hornos Caleros, 50, 05003, Ávila, Spain. Email: jlmolina@usal.es

Abstract

A comparative analysis of two different modelling approaches, System Dynamics Modelling (SDM) and Object-Oriented Bayesian Networks (OOBN) is presented, with application to aquifer management in Tunisia. Both techniques have recently become extensively used for environment and water resources modelling due to their relative advantages, mainly with regard to their flexibility, effectiveness in assessing different management options, ease of operation and suitability for encouraging stakeholder involvement. On the other hand, both approaches have several differences in the underlying mathematical background that make them complementary and/or suitable for different water and environmental systems problems. SDM is more suitable for simulating dynamics and behaviour of the processes, considering feedback loops, non-linearity, the simulation of many interacting sub-systems, or facilitating the communication with various water actors. OOBN modelling is a very powerful tool for modelling systems with uncertain inputs (or outputs) characterised by probability distributions, thus incorporating uncertainty, facilitating the use of hierarchical modelling by improving the efficiency and communication between the different parts of a model. This comparative analysis is applied to the overexploited Kairouan aquifer system in Tunisia, where the groundwater supplied by this aquifer plays an essential role for the socio-economic development in the region. Considering the geopolitical context in that area, aquifer management is becoming ever more important due to the groundwater resources being predominantly the only or most stable available fresh water source. Both models produced comparable results using the baseline data, and generally agreed on scenario tests, showing that pumping to coastal cities may prove key to reducing the current aquifer deficit. It is suggested here that water management assessment should be tackled by using both models in parallel to complement each other, adding depth and insight to results and giving a more coherent picture of the problem being addressed, allowing for more robust policy decisions to be made.

Keywords: aquifer, Object-Oriented Bayesian Networks, System Dynamics, water management.

1. Introduction

Water scarcity in semiarid regions is a serious and expanding threat to many people living in these areas. Population increases and the general consensus from climate change studies, which suggest lower rainfall totals and/or more erratic rainfall or changes to the seasonality of rainfall in critical regions such as a the Mediterranean (Arnell et al., 2004), suggest that this threat is likely to intensify in the near future. Water consumption increases with population and with local and regional development as living conditions improve, while the supply is either stable or falling, leading in some cases to 'closed basins', where the entire renewable water resource in a given hydrological basin is being exploited (Falkenmark and Molden, 2008). The total volume of groundwater resources used annually is estimated at 600-700 km^3, representing c. 20% of global water use (WWAP, 2009), and is rising rapidly, particularly in arid and semiarid regions. Many of the Northern African and Middle Eastern countries largely rely on (fossil) groundwater resources. Consequently, there is an urgent need to assess groundwater management in these critical parts of the globe. This issue has been brought up at the Rio and Dublin Earth Summits (World Water Assessment Programme, 2009). This assessment in its most basic form entails estimation of the volume of water supply and demand. Subsequently, more detailed investigations into planning and management practices (e.g. regulatory reform, policies, efforts to save water or be more efficient) can be investigated.

In this paper we compare and contrast two methods for the assessment of groundwater resources in a Tunisian aquifer that is undergoing over-exploitation. At the WaterMatex 2011 conference (8th IWA Symposium on Systems Analysis and Integrated Assessment, 19-22 June 2011, San Sebastian, Spain), discussions made clear that the development of new systems analysis and management tools is not necessarily required. More important is the proper characterisation and assessment of existing tools such that their full capabilities can be exploited. In line with this point of view, this paper contributes to the characterisation and comparative assessment of two modelling approaches applied for water resources analysis: System Dynamics Modelling (SDM) and Object-Oriented Bayesian Network (OOBN) modelling.

SDM and BNs have been previously combined for modelling water management in the same case study (Ribarova et al., 2011, Vamvakeridou-Lyroudia et al, 2009), but the application in this case was complementary and supplementary, rather than comparative. SDM was applied for simulating industrial water management, while BN modelling targeted domestic water demand. A systematic comparison of both methods applied for the same water system, with the same data, has not been published before, to the best of the authors' knowledge.

The paper is organised as follows. The two methods and modelling techniques are described (Section 2). Then the case study is introduced (Section 3) followed by descriptions of the model formulation, structure and implementation using the two methods (Sections 4 and 5). Complete descriptions of the scenarios together with the modelling results are presented in the context of the case study in Section 6. Finally, the two modelling approaches are discussed, and their suitability to groundwater assessment is assessed.

2. Methods

2.1 System Dynamics Modelling

SDM is a methodology for studying complex feedback systems. Forrester (1961) introduced SDM as a modelling and simulation methodology for long-term decision-making in dynamic industrial management problems. SDM has been applied to business policy and strategy problems (Barlas, 2002; Sterman, 2000), and to the study of complex environmental (Ford, 1999; Mazzoleni et al., 2004; Mulligan and Wainwright, 2004) and water systems (Chung et al., 2008; Li and Simonovic, 2002; Simonovic, 2002), and has been applied at a range of scales from local (Khan et al., 2009) to global (Kojiri et al., 2008; Simonovic, 2002). SDM is particularly useful when studying complex systems with many interacting elements, the behaviour of which cannot be easily predicted, if at all. It allows one to examine behaviour modes and system response as different variables are altered. As such, it is not accurate numerical prediction that is sought. Rather it is a deeper understanding of what drives system response, and how this manifests in terms of behaviour on the larger scale. This behaviour is driven by all the interconnecting elements, and not by any single factor. A classic example of the behaviour-mode type of analysis is given in The Limits to Growth (Meadows et al., 1972).

Development of SDMs typically follows an iterative approach. Initially, non-numeric models are drawn up to define the system structure and to identify the key feedbacks and causal relationships in a system. Feedback polarity between elements (positive feedback polarity represents a self-supporting loop and vice-versa) is identified. Understanding the causal structure in a SDM is critical to further model development. Quantitative models are then developed gradually until the desired level of detail and complexity is shown (Haraldsson and Sverdrup, 2004).

SDM components are described as interlinked compartments (stocks), flows (directed links) and converters (influences) (Ford, 1999). Stocks represent nodes where a material (e.g. water in a reservoir, money, population) is accumulated. Flows represent the physical movement of material into or out of stocks (e.g. river inflow or evaporation, cash deposits or withdrawals, births or deaths). Converters act to modify the rate of the flows according to some prescribed rules (e.g. evaporation rate, interest rate on a bank account or birth and death rates). Converters also act to create feedback within a system along with connecting arrows (links). The causal relationships between parameters lead to model behaviour patterns. SDM simulates a system over time by solving the mathematical functions for each element iteratively for the duration of the simulation. Due to the feedback driven nature of SDMs, the value of a stock from one model timestep influence the values of the converters, and thus the flows and stocks, at the next model timestep in a feedback loop.

The most well-known SDM packages include: SIMILE (Muetzelfeldt and Massheder, 2003), VENSIM (www.vensim.com), STELLA (www.iseesystems.com), POWERSIM (www.powersim.com) and SIMULINK – an add-on to MATLAB (www.mathworks.com). Mathematically, most existing SDM environments are similar. With the aid of graphical development environments, model development can occur with the help of non-specialist stakeholders, allowing the model to gradually develop complexity and to have a structure suited to the problem under study. Scenario testing can be easily undertaken, allowing users to fully explore a system. For example, the values in converters can quickly be altered and the model re-run to provide simulation results under new conditions. This also allows for a 'what-if' style of analysis. SDM is not explicitly spatially-based. SDM is not designed as a replacement of more specific geo-spatial models (e.g. physically-based rainfall-runoff models); it focuses rather on broad-scale system behaviour patterns than on fine-scale accurate physical representation. SIMILE (Muetzelfeldt, 2010; Muetzelfeldt and Massheder, 2003) (www.simulistics.com) has been used in this study. It attempts to overcome issues including: increased system complexity, the skill required to program a more traditional model, the lack of transparency and the lack of re-usability of existing models (Muetzelfeldt and Massheder, 2003). Ultimately, the inability of some modelling approaches (e.g. physically-based catchment models) to be able to handle many widely different, but interconnected sub-systems simultaneously (Muetzelfeldt, 2010). All of these, SIMILE (and other SDM programs) overcome by combining System Dynamics and object orientated programming.

2.2 Object-Oriented Bayesian Networks Modelling

Bayesian Networks (BNs) are based on a branch of statistics developed in the 18th century by Thomas Bayes and have been around since 1921. BNs have been used as a modelling tool as part of the development of decision support systems in diverse fields such as medicine, road safety and artificial intelligence; however, they have not been widely applied to environmental systems until recently (Ordoñez Galán et al., 2009). Increasingly, BNs are being used to model diverse problems of high complexity for water management applications (Varis and Fraboulet-Jussila, 2002; Borsuk et al., 2004; Little et al., 2004; Bromley et al., 2005; Martin de Santa Olalla et al., 2006; Castelletti and Soncini-Sessa, 2007; Henriksen and Barlebo, 2007; Ticehurst et al., 2007; Farmani et al., 2009a; Malekmohammadi et al., 2009; Morteza Mesbah et al., 2009, Vamvakeridou-Lyroudia et al, 2009).

BNs can be defined as a graphical representation of Bayesian probabilities, formally known as ‘Directed Acyclic Graphs’ (Cain, 2001; Molina et al., 2010). The acyclic part in this definition is crucial, as it implies a lack of ability to handle feedback. This technique is found to be applicable as a type of Decision Support System (DSS) based on a probability theory which implements Bayes’ rule (Pearl, 1988; Bayes, 1991; Jensen, 1996; Jensen, 2001). The multilateral properties of BNs allow their use in resource and environmental modelling (Varis and Kuikka, 1999). Cain (2001) defined BNs as "some nodes that represent random variables that interact with others. These interactions are expressed like connections between variables". The use of BNs presents a series of advantages over other environmental DSSs (Bromley et al., 2005; Castelletti and Soncini-Sessa, 2007; Molina et al., 2010). According to Borsuk et al. (2004), the graphical structure explicitly represents a cause–effect relationship between system variables that may be obscured under other approaches.

A BN consists of three main elements: (1) a set of variables representing the factors relevant to a particular environmental system; (2) the relationships between these variables that quantify the links between variables; and (3) the set of conditional probability tables (CPTs) quantifying the links between variables that are used to calculate the state of nodes. The first two elements form a Bayesian Diagram and the addition of the third forms a full network. The CPTs are defined within the BN modelling software based on the characteristics of the input data used.

Object-Oriented Bayesian Networks (OOBNs) are an advance on traditional BNs based on Object-Oriented Programming (Molina et al., 2010). OOBNs are hierarchical descriptions of real-world problems that mirror the way in which humans conceptualise complex systems. To cope with complexity, humans think in terms of hierarchies of different classes (Molina et al., 2010). There are several important features that characterise the use of OOBNs over traditional BNs. First, they allow consideration of the uncertainty in every single variable of the models through the implementation of the CPTs, which allows for the possibility of taking into account the error or noise in the variable(s). For hydrological processes this can become important due to the stochastic nature of the processes. Encapsulation of the internal details of a class means that some objects can be hidden and only those objects required for interfacing with other classes need to be exposed, making the modelling environment more user-friendly. Inheritance allows a class to inherit the attributes and methods of another class. Polymorphism allows objects to be of different types or nature, allowing a more accurate representation of the real-world. This means for instance that economic, physical, social and other variables can all be represented together, something which is essential if real-world environmental problems are to be realistically modelled. A further feature is that because systems are often composed of collections of identical or almost identical components, models of many systems contain repetitive patterns and the notion of instance nodes makes it very easy to construct multiple identical instances of a network fragment.

Although traditional BNs are not intended for dynamic analysis, which forms one of its main disadvantages, 'time slicing' techniques provide one way to generate predictive simulations. In this sense, dynamic BNs work like Markov Chains of multiple time order (Petri nets) that are aimed to be a transient way of BN modelling, considering each time step of a transient and/or predictive model (Molina et al., 2011a). OOBNs can be easily coupled with other simulation or optimisation models (Farmani et al., 2009b; Molina et al., 2011b), tools or algorithms. Finally, the BN representation through a graphical display makes communication between stakeholders or water actors simple, thus promoting their involvement in water management problems.

Table 1 compares the main features of the SDM and OOBN approaches. Both modelling approaches have been used widely in order to assist in (sustainable) aquifer/groundwater management studies, illustrating the applicability of each method to the present study (e.g. Stave, 2003; Henriksen et al., 2007; Khan et al., 2009; Martinez-Santos et al., 2010).

3. Case Study description and model development

The same case study has been formulated in each modelling approach using the same input data. The case study is the Kairouan aquifer region in Tunisia, covering an area of c. 3000 km^2 (Figure 1). Rainfall is low (c. 300-500 mm yr^{-1}, with variability of 100-700 mm yr^{-1}) and falls in discrete, intense showers. The Kairouan aquifer, which is the main stable water source in the region, is subject to over-abstraction with the water table in the area observed to be dropping (Le Goulven et al., 2009), with subsequent impacts on water quality and future water availability. Agriculture is the largest regional water user, accounting for 80% of local water consumption (Chahed et al., 2008), and is the main socio-economic activity. Domestic and industrial uses make up the remainder of the local consumption with both forecasted to increase. Officially, re-use of treated waste water is not permitted for either domestic or irrigation use due to concerns over the quality of the returning water. Despite this, a fraction is re-used due to illegal recharge and leakage from pipes and tanks. There is also a small, but critical natural water demand which goes to maintaining fragile *sebkha* (salt-flat/marsh) regions. Protecting this fragile ecosystem type is critical, but depends strongly on available water (quality) from the aquifer. Modelling may help determine if these sensitive regions may be threatened in the near future as a result of aquifer overexploitation.

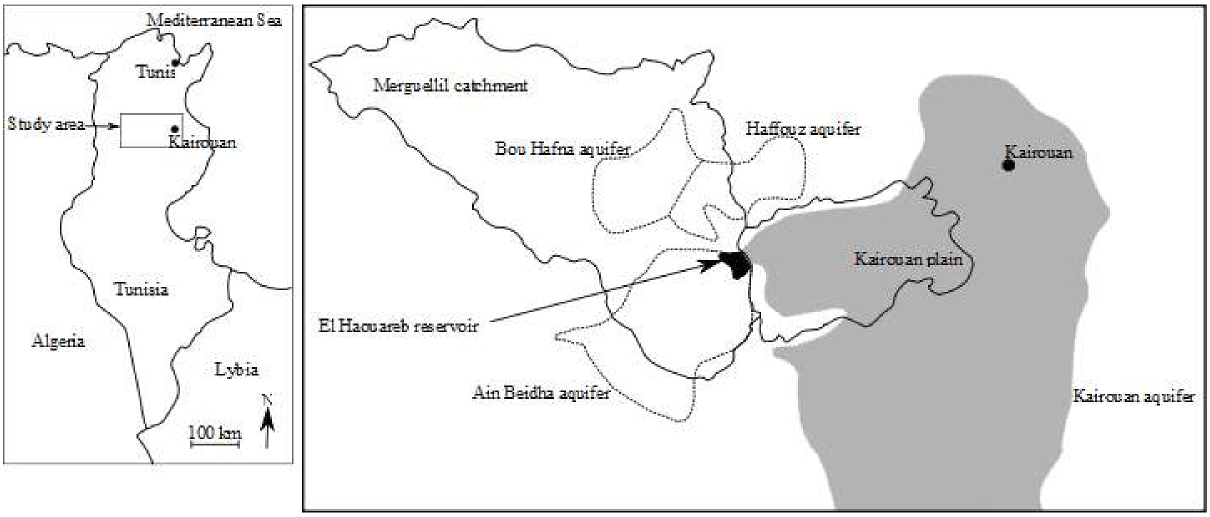

Figure 1: Map showing the Tunisia case study area.

Once local water uses have been accounted for, most of the remaining water is pumped out of the Kairouan aquifer and transferred to the coast in order to satisfy the water demands of tourist resorts (e.g., swimming pools, golf courses). This transfer represents volumetrically the major abstraction from the aquifer, and is the main reason for the current overexploitation. Current government policy is to reduce this pumped volume by c. 50% by 2030 in an attempt to reduce the water deficit.

The SDM used here is a simplified version of a more complex model developed for the European Commission Seventh Framework (EC FP7) research project 'Water Availability and Security in Southern Europe and the Mediterranean (WASSERMed) (Susnik et al, 2012). The WASSERMed model has been simplified for the purposes of this comparative study. The WASSERMed model was developed closely with local Tunisian project partners and stakeholders INAT (Institut National Agronomique de Tunisie). Model development represents a cooperative, participatory effort, with the local experts informing on critical aspects of the model structure and the available data for different parts of the model. They also gave critical information regarding potential policy measures aimed at reducing future water demand. Model development was carried out in stages, each stage iteratively assessed and improved in participatory mode. So, at each stage the model was assessed by INAT to ensure that the Kairouan system was being accurately represented, and to ensure that model behaviour was representative according to local knowledge and observation. Several iterations were completed until the model was deemed satisfactory by INAT and the research team (University of Exeter) alike. It is noted that before any quantitative model development took place, conceptual (Vamvakeridou-Lyroudia et al, 2008) and causal loop (Susnik et al, 2012) modelling was conducted. This was done in order to help define the system boundaries and key interactions, to help define data requirements, and to act as a guide for quantitative model development. There are other examples of SDMs being developed in a cooperative nature with close guidance from local experts and stakeholders (e.g. Ahmad and Simonovic, 2000; Stave, 2003; Tidwell et al., 2004).

OOBN model development was largely informed by the developments of the SDM as it was not part of the WASSERMed project. The key SDM aspects (i.e. the various interconnections and feedbacks, inflows, demands) were used to inform the OOBN model structure and connections. However, the OOBN was developed in a way viable and suitable for OOBN representation. Therefore, the two models do not agree exactly in structure. As with SDM, there are also examples of OOBNs being developed in a participatory, cooperative nature (e.g. Castelletti and Soncini-Sessa, 2007; Henriksen et al., 2007; Ross and Martinez-Santos, 2010).

4. SDM implementation

For the purposes of this comparison, a simplified version of a more complicated SDM developed for the Kairouan aquifer (Sušnik et al., 2011a; Sušnik et al., 2011b, Sušnik et al, 2012) has been implemented (Section 3 and Figure 2a). Sufficient information has been retained to suggest that model results should correlate closely to those from the more comprehensive model. It is noted that the behaviour of the model in terms of the pattern of water volume in the Kairouan aquifer over time is more important than accurate numerical prediction of water volumes. It was critical to ensure that the simplified model still exhibited sufficient complexity, and that it integrated the water-balance aspect with socio-economic concepts.

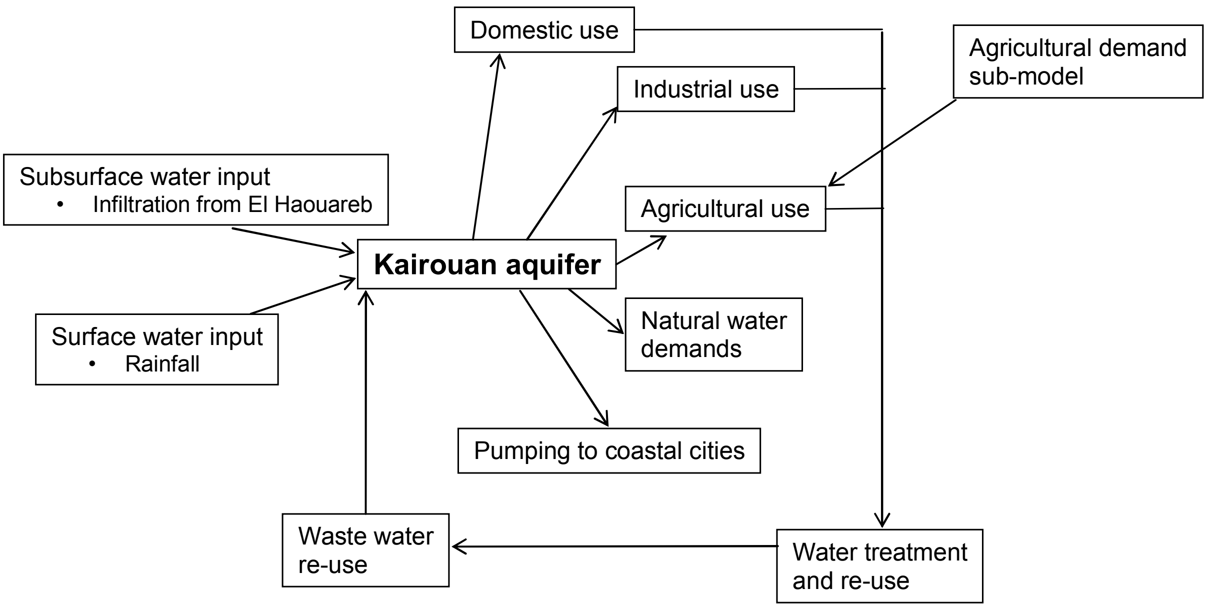

Figure 2a: Schematic representation showing the main links and relationships in the SDM implemented here. This does not show the full complexity of the model. Agricultural water demand is predicted using a more complex separate sub-model (Figure 2b).

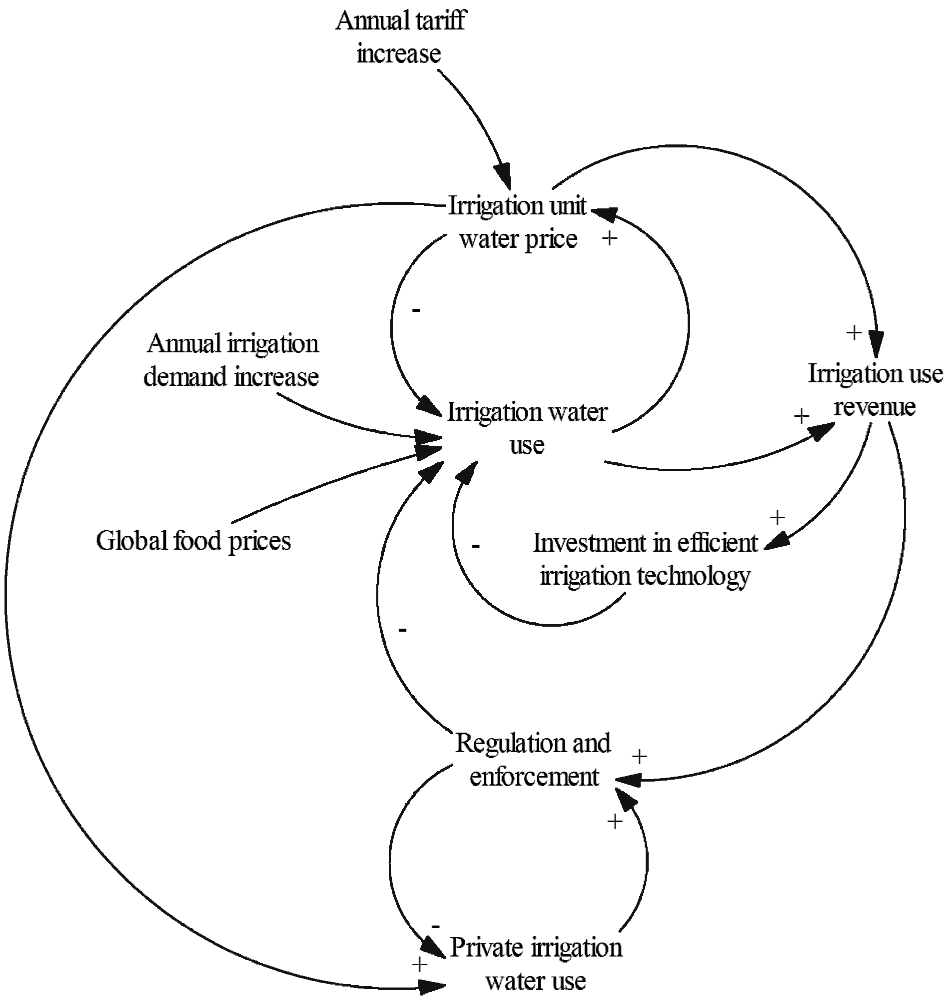

Figure 2b: Causal loop diagram illustrating the complexity of the agricultural demand sub-model. Arrows are labelled with polarity. Positive polarity indicates positive feedback, and vice-versa.

The main simplifications from the WASSERMed model (Sušnik et al., 2011a, b; Sušnik et al., 2012) are related to the aquifer inputs, and the domestic, industrial and coastal pumping demands. In these cases, the complex sub-models from the WASSERMed model have been replaced with time-series' and therefore do not exploit the full utility of SDM. However, the agricultural demand sub-model has been retained (Figure 2b), for three reasons: i) it allows some investigation into the complexity of this sub-system, utilising the capability of SDM to represent feedback loops and non-linearity; ii) agriculture is the main water consumer in the region, and is the dominant economic activity with socio-economic implications; and iii) the model is still simple enough to allow for meaningful comparison with the OOBN model, but also allows for good contrast of the relative merits of the two modelling paradigms.

The SDM (Figure 2) includes as inflows: infiltration leakage from the El Haouareb dam and; infiltrating rainfall. These are the two most significant inputs to the aquifer, of which leakage from the dam is dominant. The El Haouareb dam, due to high evaporation rates, over-use and leakage down a fissure at the downstream end of the dam, has been (nearly) empty for parts of the last decade. The volume of leakage is estimated at about 50% of any water stored behind the dam (Leduc et al., 2007), and it is this volume that is used in the model as recharge. The rainfall contribution is highly uncertain. Rain does not fall evenly, rather it falls in discrete 'cells' covering only a fraction of the catchment. For this study, a value of 5% coverage (i.e. the proportion of the catchment area over which rains fall) was assumed with guidance from local partners in INAT during the model development process.

As outputs from the aquifer, the model incorporates domestic, industrial and agricultural water uses, water transfers to the coastal cities and 'natural' outflow that accounts for the sebkha regions. In addition, there is a waste-water reuse feedback loop. The proportion of this reuse is estimated at 10% of the water use in each sector (Chahed et al., 2008). The wastewater reuse acts as input to the aquifer with a time-delay of one time unit (i.e. one month, as it cannot be used as input until the water has been extracted). The simulation time step is monthly.

The complex agricultural sub-model has been retained (Figure 2b). Agricultural water demand is influenced by, and influences a number of factors. Agricultural demand changes per time step according to official predictions of annual water demand change. It also changes in response to global food prices. The logic here is that an increase in global food prices leads to an increase in agricultural water demand as farmers grow more crops in order to exploit the higher prices. Farmers also raise their prices to offset increases in the water tariff, thus affecting food prices. Additionally, demand is affected by the water tariff. The tariff increases by a given percentage annually, and is influenced by the water consumption. The equation for price elasticity of demand equation was used to estimate the change in water demand. For example, by doubling the tariff increase per timestep, the demand is decreased at each timestep according to the price elasticity of demand equation (Lipsey and Chrystal, 1999):

$$\Delta D = D_{t-1} \text{ x } \{PeoD_t \text{ x } (\Delta P/P_{t-1})\}, \qquad (1)$$

where D_{t-1} is the demand at time step t-1, P_{t-1} is the tariff at time step t-1, $PeoD_t$ is the price elasticity of demand at time step t. ΔD and ΔP represent the change in water demand and tariff from the previous timestep respectively. PeoD was set to -0.3, representing an inelastic market. The demand and the tariff contribute to the revenue generated from agricultural water use. Of this, a proportion is invested for efficient irrigation techniques, which acts to reduced demand (assuming that either cropping intensity or cropped area do not increase). Also, some revenue is invested for water regulation and law enforcement. Greater levels of enforcement and regulation may help to lower consumption. Finally there is the 'private' irrigation use which is not regulated, and sometimes illegal. It is assumed that higher tariffs will lead to increased private demand as farmers seek to reduce costs, although this trend can be influenced and mitigated by better regulation and particularly, better enforcement. Thus, this sub-model represents a complex system where the main factor of interest (the agricultural demand) is influenced by, and influences, many other factors in the sub-model, including governance issues. The value for demand at each timestep is fed into the main aquifer water-balance of Figure 2a.

5. OOBN model implementation

The OOBN model (Figure 3) describes an aggregated model representing the Kairouan aquifer water budget, incorporating uncertainty through conditioned probability in every variable. The OOBN model is divided in three main parts and two classes. The inputs to the aquifer and the outputs from the aquifer are included in the first class, and a third part that represents agricultural demand (Figure 3b) is designed as the second class. The difference between inputs and outputs represents the aquifer water budget, represented by the variable "Kairouan aquifer GW Budget" (Figure 3). Furthermore, this allows the indirect estimation of the cumulative status of aquifer storage over time.

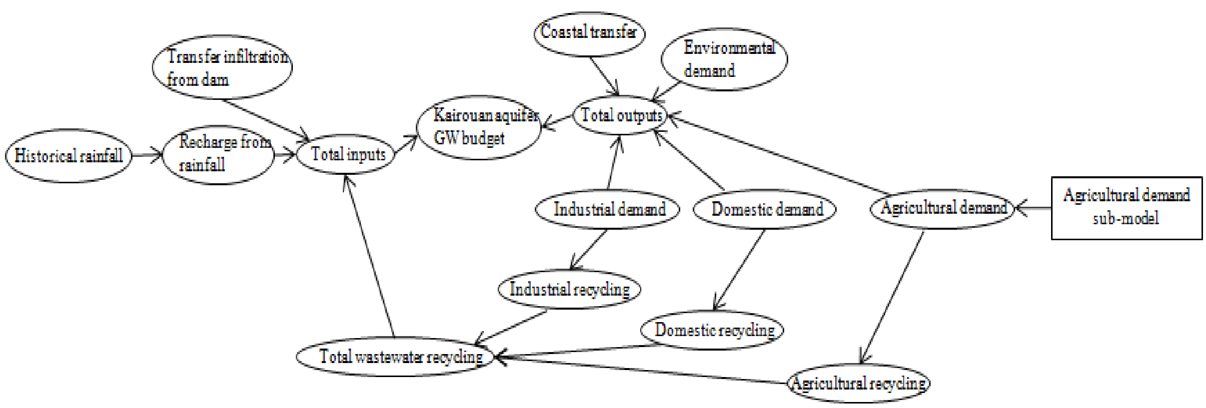

Figure 3a: The OOBN model. Note the agricultural sub-model is represented as a separate class (square box, Figure 3b).

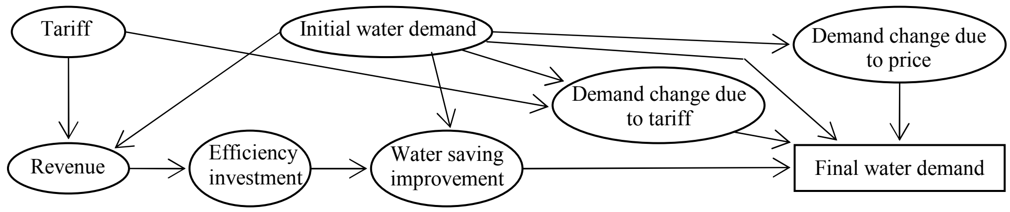

Figure 3b: Detail of the BN agricultural sub-model. Note the lack of feedback when compared with the SDM version (Figure 2b).

The OOBN includes as inflows to the aquifer (Table 2): infiltration leakage from the El Haouareb dam, recharge produced directly from rainfall and the volume of wastewater recycling that is returned to the aquifer. Like the SDM implementation, leakage from the dam and recharge from rainfall are the two most significant inputs to the aquifer, of which leakage from the dam is probabilistically dominant in the BN model.

As outputs from the aquifer, the model incorporates (Table 2) domestic, industrial, agricultural demands, water transfers to the coastal cities and natural outflow accounting for environmental water requirements. The agricultural demand is abstracted to a separate sub-model (class) (Figure 3b), and accounts for change to tariff, revenue, and savings from investment and water saving measures.

Probability distributions for each variable were calculated according to the following general criteria. First, the timeframe is monthly. Second, the probabilistic discretisations were created considering same range intervals for all nodes. Finally, the data records for all variables involved in the model are three years in length.

Specific criteria in regards to each variable are as follows. First, the controlling factor rainfall, is not conditioned by any other variable, so the three year time series was discretised in five intervals from 0 to 80 mm per month. The other parent node that is not conditioned is the transfer infiltration from the dam which has been discretised in four equal range intervals from 0 to 12 m^3 per month. Furthermore, all the outputs that represent the abstraction from the aquifer were also considered as parent nodes (except the agricultural demand, explained below), which means that they are not influenced by other nodes. The industrial demand is made up of five intervals from 0.012 to 0.018 m^3 per month, domestic demand varies from 0.49 to 0.73 m^3 per month, coastal transfer from 1.8 to 2.76 m^3 per month and environmental demand is considered as a constant value of 0.63 m^3 per month.

The rest of the variables are conditioned by other variables, so their probability distributions are defined by Conditioned Probability Tables (CPTs) under the Bayes Theory (Molina et al., 2010). CPTs can be calculated in different ways: from real observation; by outputs from other models; or by expert opinion. In this case, for the input nodes the CPT associated with the "Recharge from rainfall" node has been estimated using data provided by local Tunisian partners. CPTs for agricultural, industrial and domestic water reuse nodes have been calculated by means of a constant coefficient of 10% of the corresponding demand. In this case, CPTs were calculated using arithmetic expressions such as *agricultural_demand* 0.1*; *industrial_demand*0.1* and *domestic_demand * 0.1*, respectively. The summation of the three recycling nodes was made by a node named "Total Wastewater recycling" that has been discretised in three intervals from 0.05 to 0.2 m^3 per month. All the inputs to the aquifer are summed in a node called "Total Inputs". Finally, the goal of the whole OOBN model is established through the node "Kairouan aquifer GW Budget". The probability distribution is made up of ten intervals from -6 to 14 x 10^6 m^3 per month.

Agricultural demand is considered in a separate sub-model which represents a second class, coupled with the first class through an instance node called "Final Agricultural Water Demand". This class comprises two parent nodes. First, the node "Initial Agricultural Water Demand" represents the original water demand for agriculture at the beginning of the model time frame; "Water Tariff" expressed in units of the local currency (Tunisian Dinars, TD) per cubic meter represents the water price for agricultural activities. Both nodes condition the "Agricultural Water Revenue" (TD), which drives the node "Efficiency Irrigation Investment". The node "Improvement Water Efficiency Savings" is a child and consequently depends on the nodes "Investment for Efficiency Investment" and the "Initial Water Demand". The node "Water Demand Change due to Water Price" is dependent on "Water Tariff" and "Initial Agricultural Water Demand".

6. Results

For both model formulations, datasets representing the latest three years of data available (2004-2007), which were provided by local partners INAT, were simulated first to define a baseline scenario against which a suite of hypothetical scenarios were then compared. This section presents the results from the OOBN model simulations, followed by the results from the SD modelling. During the various scenarios, only the values being tested where changed. All other values were defined by baseline data.

6.1 OOBN model

6.1.1 Baseline

The average value for the leakage from El Haouareb dam to the aquifer is 2.42 x 10^6 m^3 per month. The leakage is shown to increase over the time during the simulation, suggesting that this component is becoming more important for water management in the area. Average rainfall is 24.89 mm/month and it contributes c. 0.47 x 10^6 m^3 per month to aquifer recharge (Figure 4a), but with large uncertainty. The average value of wastewater return to the aquifer is estimated at 0.13 x 10^6 m^3 per month. With regard to abstractions, the most important demand is the coastal transfer with an average value of 2.28 x 10^6 m^3 per month, although there is considerable variation.

Regarding agricultural water use, the demand is c. 0.78 x 10^6 m^3 per month (Figure 4b). Agricultural water revenue is c. 47212 TD per month and water savings due to improvement in water efficiency are c. 4298 m^3 per month.

The baseline analysis of the Kairouan aquifer budget shows a negative value of -1.33 x 10^6 m^3 per month (-15.96 x 10^6 m^3 yr^{-1}), implying decreasing aquifer storage and the consequent depletion of reserves. This value is close to that produced by the SDM baseline simulation (Section 6.2.1), and agrees well with other observations (Leduc et al., 2007).

To be cited as: Sušnik, J., J.-L. Molina, L.S. Vamvakeridou-Lyroudia, D.A. Savić and Z. Kapelan (2012) Comparative analysis of System Dynamics and Object-Oriented Bayesian Networks modelling for water systems management. Water Resources Management, Vol 27, No 3, pp. 819-841.

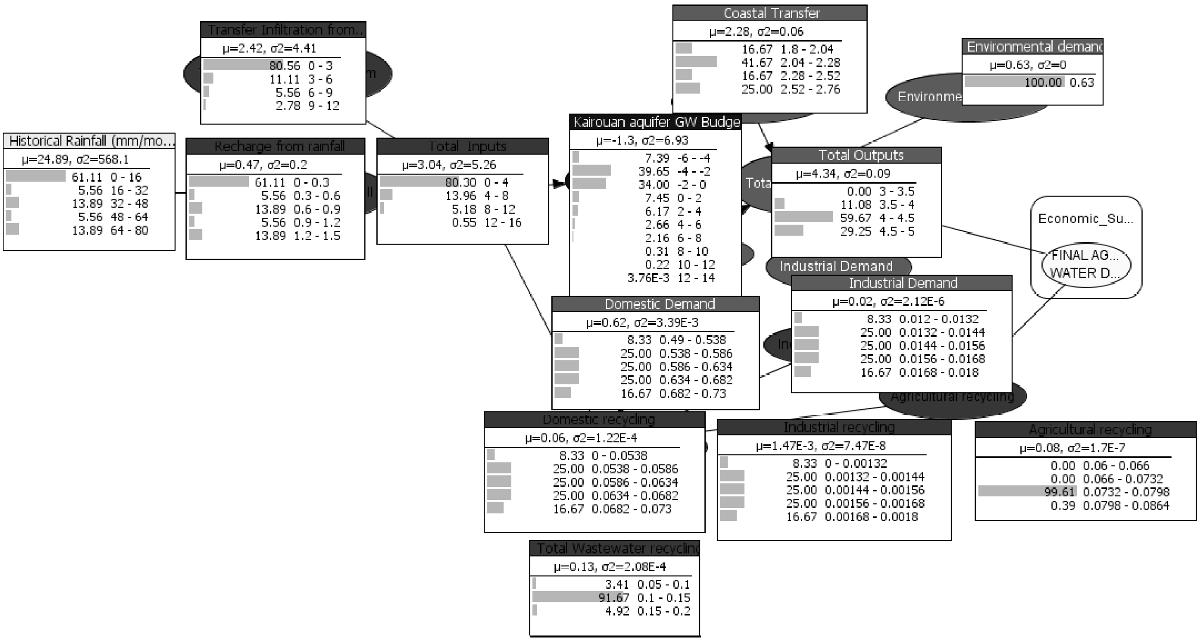

Figure 4a: Baseline results for the OOBN model.

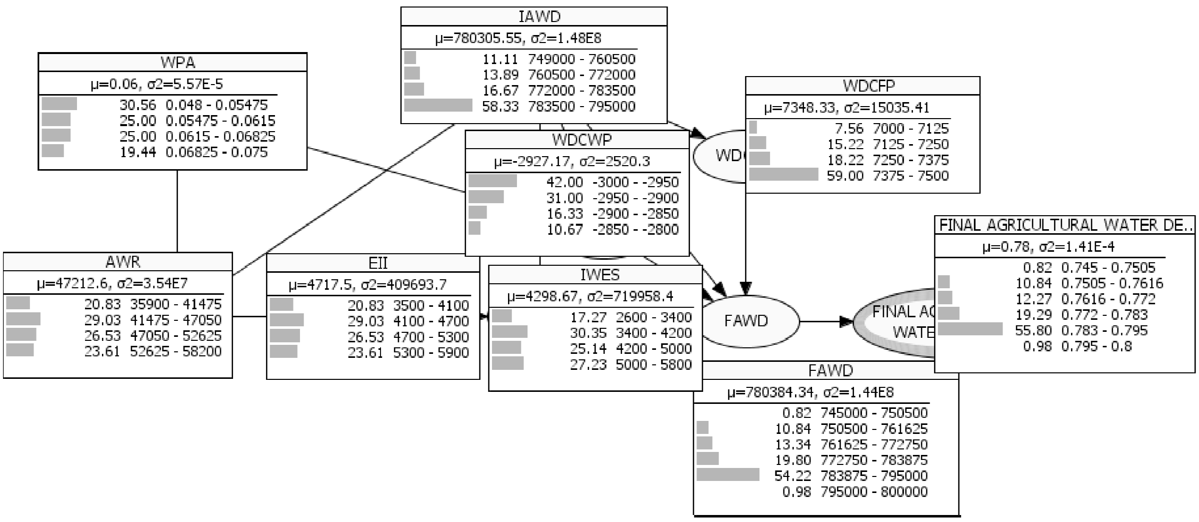

Figure 4b: Baseline results for the agricultural sub-model in the OOBN.

6.1.2 Hypothetical model scenarios

The scenarios here represent hypothetical water management options, and are not reflective of actual policies being implemented in Tunisia. The scenarios were designed to minimise or maximise the main variables of the system which were deemed to be, for the inputs: the transfer infiltration from El Haouareb, for the outputs: the coastal transfer and finally, as the objective: the Kairouan aquifer water budget. These scenarios are defined as follows:

1. Maximization of the leakage infiltration from the dam

The monthly leakage volume from the upstream El Haouareb dam was maximised (i.e., make it as large as possible within CPT constraints).

2. Minimisation of the leakage infiltration from the dam

The monthly leakage volume from the upstream El Haouareb dam was minimised (i.e., make it as small as possible within water balance constraints set by the CPTs).

3. Maximisation of the coastal transfer

The objective was to maximise the monthly transfer of water to the coastal cities (i.e., make it as large as possible within water balance constraints set by the CPTs).

4. Minimisation of the coastal transfer

The objective was to minimise the monthly transfer of water the coastal cities (i.e., make it as small as possible within water balance constraints set by the CPTs).

5. Maximisation of the Kairouan aquifer water budget

With this scenario, the objective was set such that the monthly volume of water held in the aquifer was as large as possible. This meant that the OOBN adjusted influencing inputs to make them as large as possible while outputs were adjusted to make them as small as possible, all within the constraints of the CPTs.

6. Minimisation of the Kairouan aquifer water budget

With this scenario, the objective was set such that the monthly volume of water held in the aquifer was as small as possible (an undesirable situation). The OOBN model adjusted inputs to make them as small as possible. Outputs were adjusted to make them as large as possible.

The maximisation and minimisation of variables is achieved by assigning 100% chance to the highest and lowest interval of the variable, respectively. For example, in order to maximise the variable "leakage infiltration from the dam", a 100% chance for the highest interval (9-12 m^3 $month^{-1}$) was assigned.

The impacts of minimising or maximising the main variables on the volume of water held in the Kairouan aquifer produced by every scenario are shown as probabilistic distributions in Figure 5 and are explained as follows:

1. Maximization of the leakage infiltration from the dam (Figure 5a)

The main impact of this scenario is in increase to the Kairouan aquifer water budget by 8 x 10^6 m^3 per month when compared to the historical average. This leads to recharge of 6.45 x 10^6 m^3 per month (77.16 x 10^6 m^3 yr^{-1}).

2. Minimization of the leakage infiltration from the dam (Figure 5b)

The main impact of this scenario is a reduction in the Kairouan aquifer water budget by 2.24 x 10^6 m^3 per month, leading to an annual deficit of -26.88 x 10^6 m^3.

3. Maximization of the coastal transfer (Figure 5c)

The main result from this scenario suggests a Kairouan aquifer budget decrease (i.e. greater net deficit) to a value of -1.7 x 10^6 m^3 per month (-20.4 x 10^6 m^3 yr^{-1}).

4. Minimization of the coastal transfer (Figure 5d)

The main impact resulting from this scenario was a lower net annual aquifer deficit of -0.89 x 10^6 m^3 per month (-10.68 x 10^6 m^3 yr^{-1}).

5. Maximization of the Kairouan aquifer water budget (Figure 5e)

There are two main impacts from this scenario: first, an increase in the infiltration from El Haouareb to an average rate of 10.5 x 10^6 m^3 per month; and second, a reduction to the coastal transfer to a rate of 1.93 x 10^6 m^3 per month. This scenarios does not produce a significant impact on the socioecomic agricultural sub-model.

6. Minimization of the Kairouan aquifer water budget (Figure 5f)

Again, there are two main impacts produced by this scenario: a reduction of the infiltration from El Haouareb to an average rate of 1.57 x 10^6 m^3 per month and; a small increase to the coastal transfer to a rate of 2.43 x 10^6 m^3 per month.

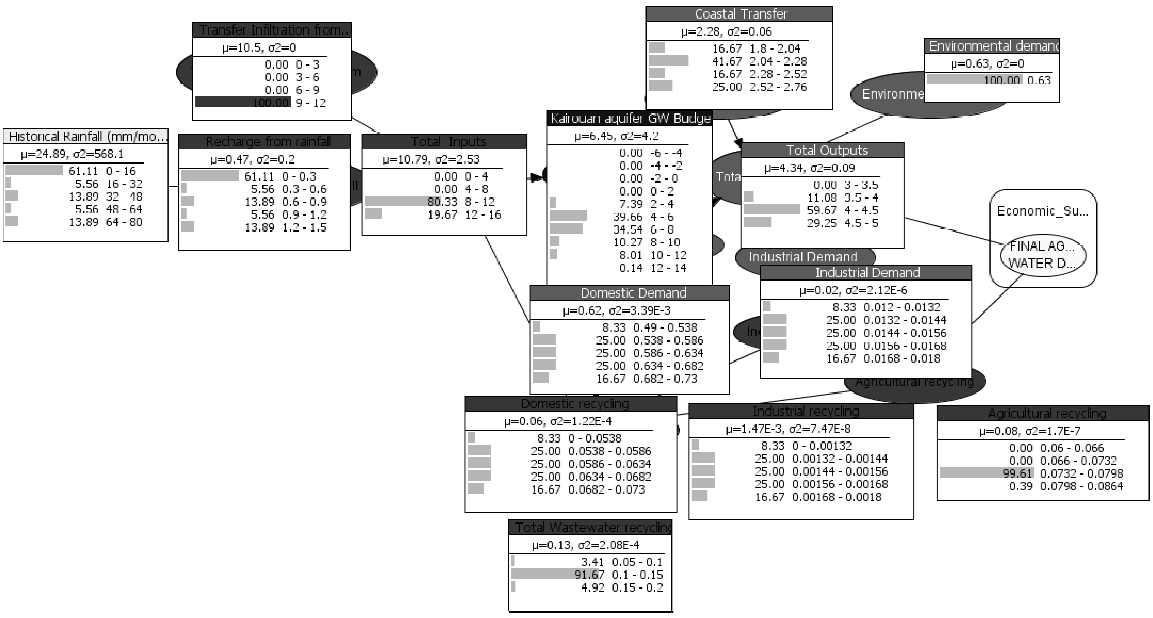

Figure 5a: OOBN results for hypothetical test 1 - maximisation of leakage infiltration.

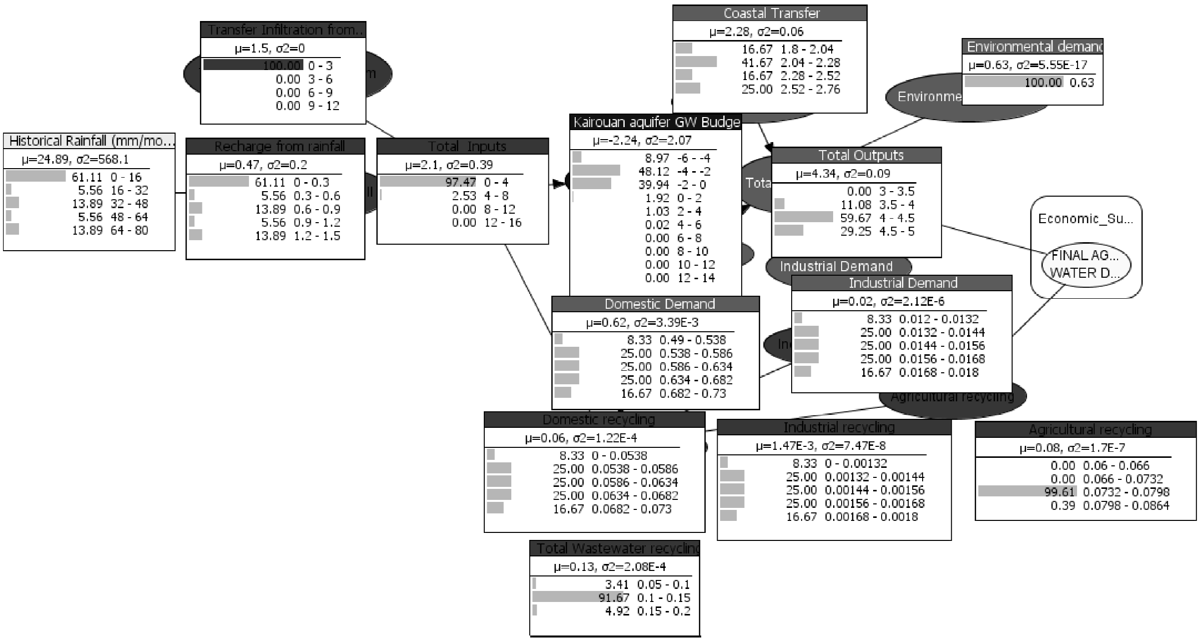

Figure 5b: OOBN results for hypothetical test 2 - minimisation of leakage infiltration.

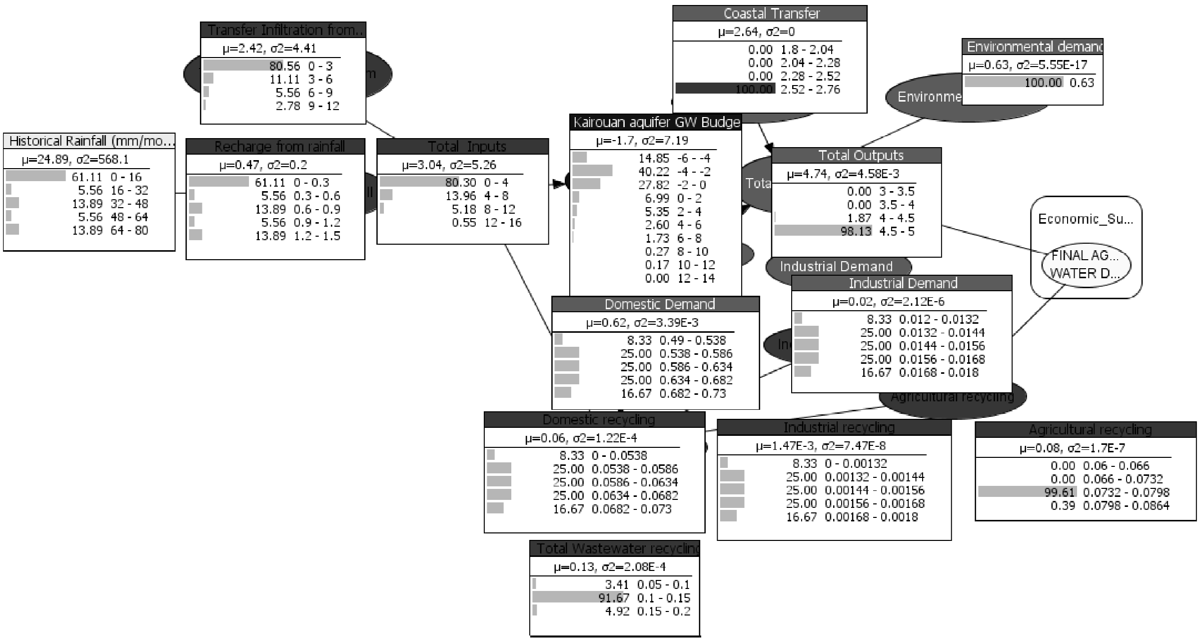

Figure 5c: OOBN results for hypothetical test 3 - maximisation of coastal transfer.

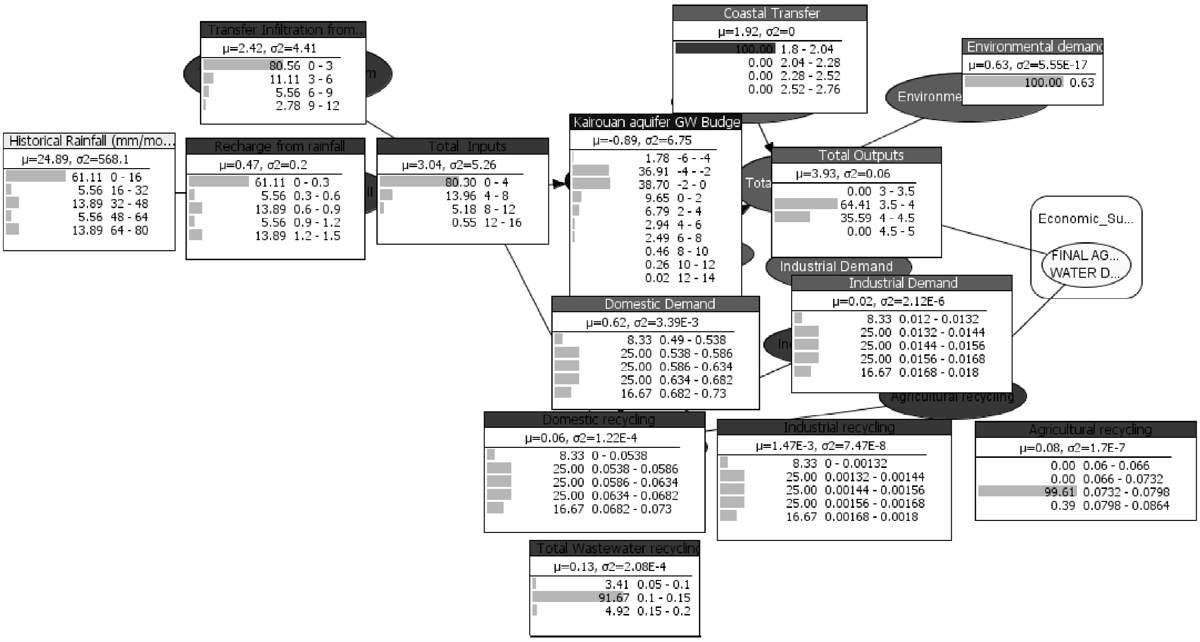

Figure 5d: OOBN results for hypothetical test 4 - minimisation of leakage infiltration.

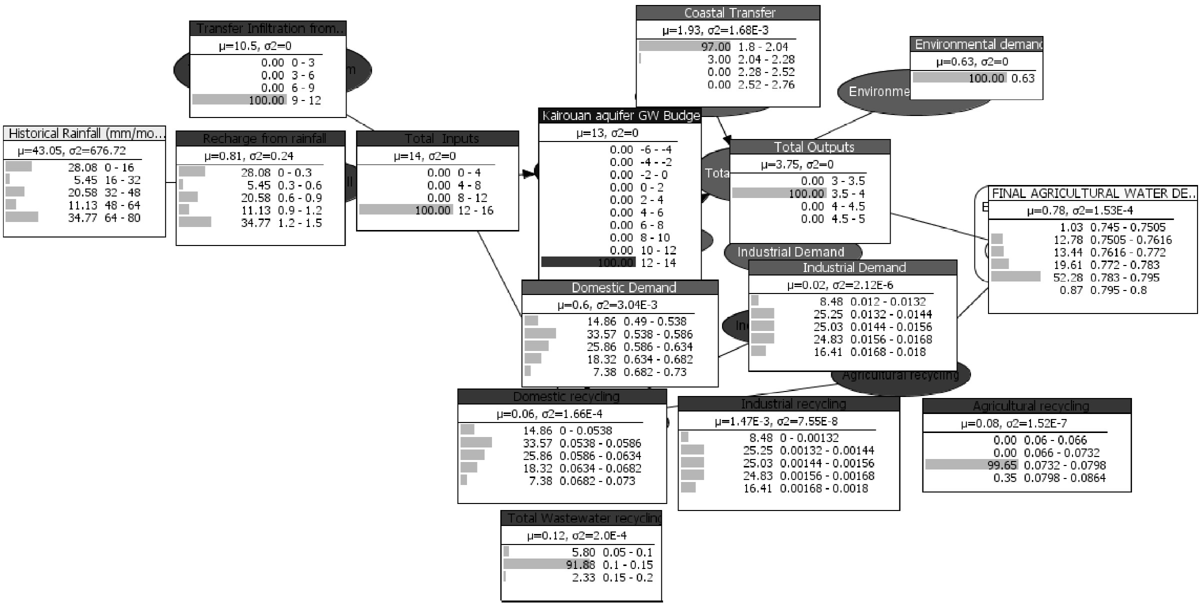

Figure 5e: OOBN results for hypothetical test 5 - maximisation of the Kairouan aquifer water budget.

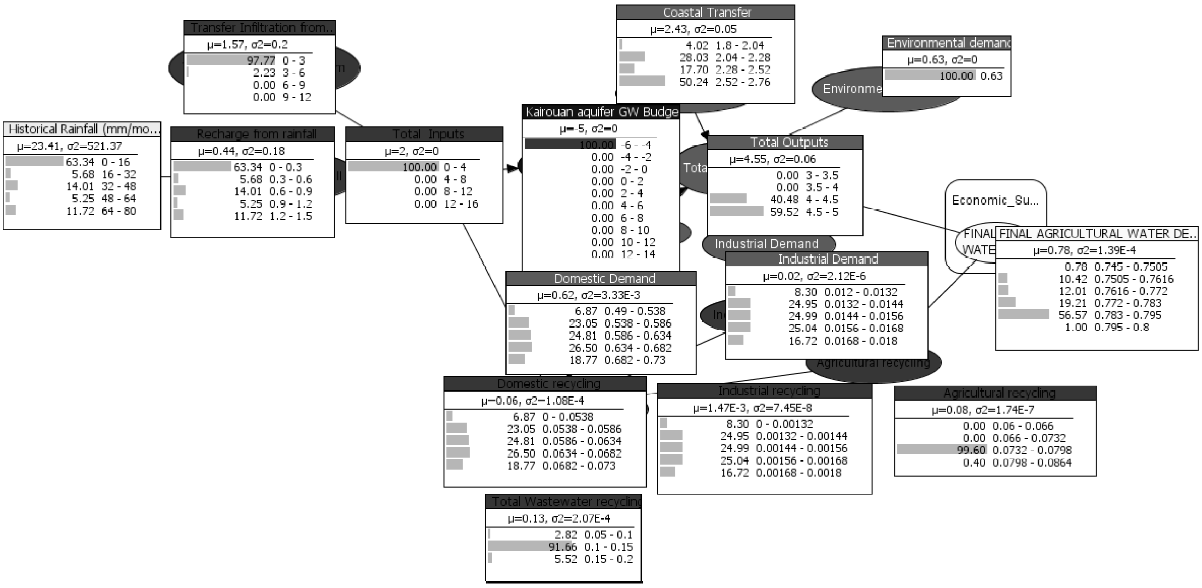

Figure 5f: OOBN results for hypothetical test 6 - minimisation of the Kairouan aquifer water budget.

6.2 System Dynamics Model

6.2.1 Baseline

Figure 6 show the time-series' for the model inputs, outputs and aquifer water volume. For the most part, the aquifer is being over-exploited, with demand exceeding supply. The average annual water deficit is estimated at c. 10.3 x 10^6 m^3, which corresponds reasonably to other published results (Luc, 2005). The pattern of the model result is similar to observations of local water-table levels from piezometric readings (Le Goulven et al., 2009). Thus, the SDM is representing the current system behaviour well.

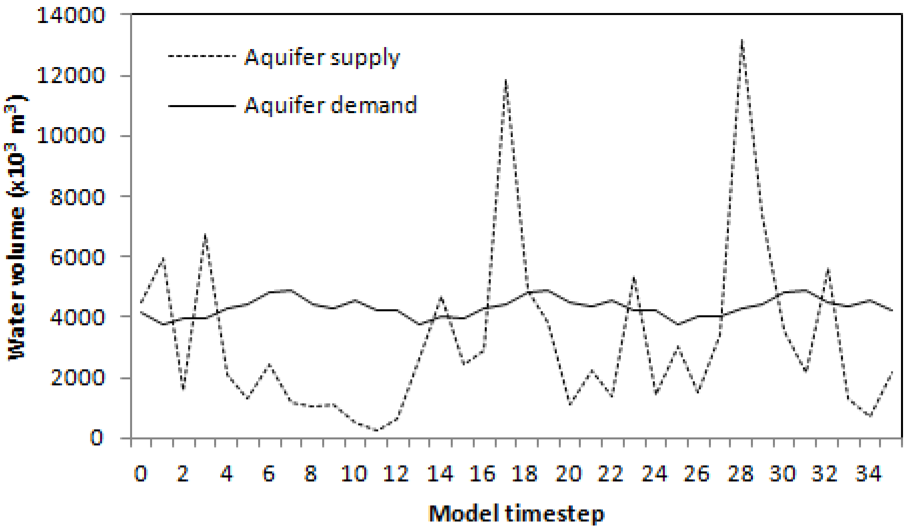

Figure 6a: Time-series of aquifer inputs and outputs for the baseline SDM scenario.

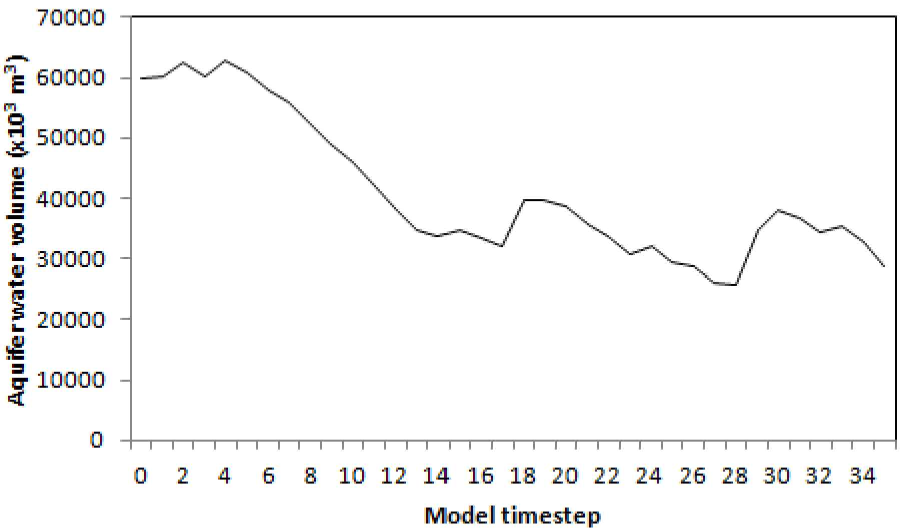

Figure 6b: Time-series showing the evolution of aquifer water volume for the baseline SDM scenario.

6.2.2 Hypothetical model scenarios

Using SDM, a suite of tests were performed that aimed to shed light on the impacts of changing various parameters. Of particular importance here are the impacts from agricultural demand, so that the complex sub system, with interlinked, feedback-driven structure, could be explored. The simpler input/output parameters are dealt with first, followed by analysis of the agricultural demand sub-model.

6.2.2.1 Input rainfall

For this model run, predictions of rainfall in 2050 from a regional climate model were used (a regional climate model was forced by ECHAM5 with the IPCC A1B emissions scenario. Data were provided at monthly timestep with a resolution of 25x25 km by CMCC, a WASSERMed partner). Rainfall totals are 19% lower with respect to the baseline. Under this scenario, the deficit increases to c. 13 x 10^6 m^3 yr^{-1} (Figure 7).

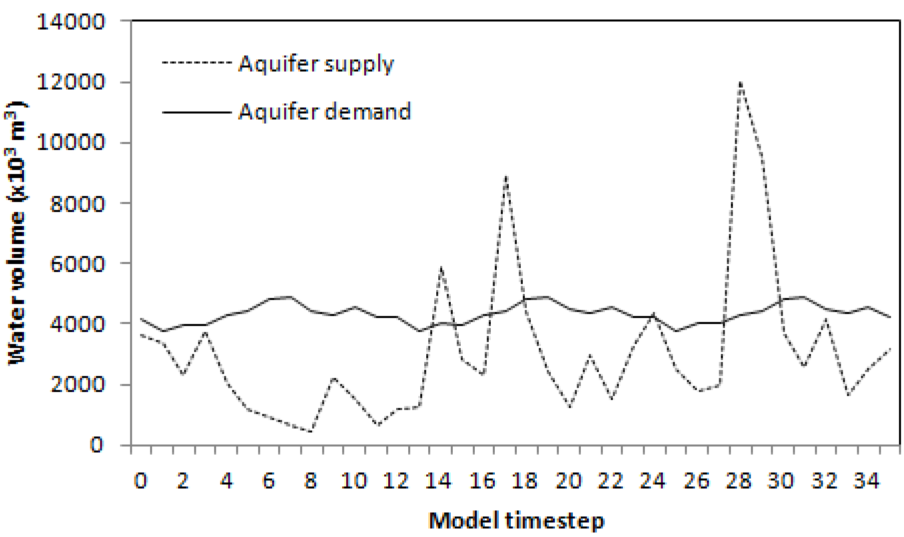

Figure 7a: Showing the supply to and demand from the Kairouan aquifer under predicted future rainfall.

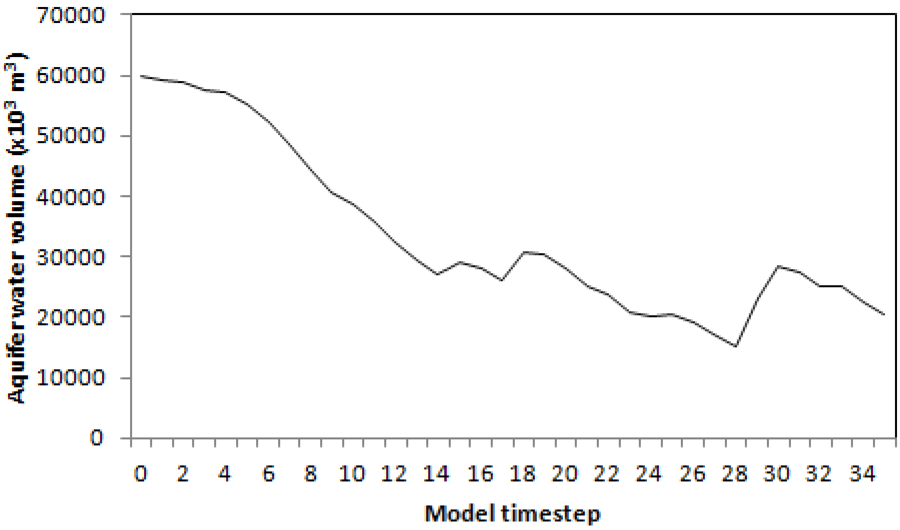

Figure 7b: Simulated evolution of the aquifer water volume under future rainfall conditions.

6.2.2.2 Domestic and industrial demand

For this series of tests, the baseline industrial demand was doubled and halved, while the domestic demand was changed by factors of 0.5, 0.8, 1.2 and 2. When industrial demand was halved, the average annual aquifer deficit was c. 10.1 x 10^3 m^3 yr^{-1}. When it was doubled, the deficit was c. 10.4 x 10^3 m^3 yr^{-1}. For the domestic demand tests, the aquifer water deficit ranged from 7 x 10^3 m^3 yr^{-1} to 16.7 x 10^3 m^3 yr^{-1} as demand was scaled from 0.5 to 2 times baseline respectively. Due to the relatively small domestic and industrial water demand, doubling or halving the present values for domestic and industrial use had relatively little impact on the deficit, and a pattern of over-abstraction is simulated in all cases.

6.2.2.3 Pumping to coastal cities

Volumetrically, pumping water to coastal cities is the largest exploitation of the Kairouan aquifer. The baseline pumping was scaled from 0.6 to 1.4 of the baseline value at increments of 0.2. As a result of these changes, the water balance ranged from 0.4 x 10^6 m^3 yr^{-1} to -20.9 x 10^3 m^3 yr^{-1}. By reducing pumping by 40%, net recharge can be achieved. However, if pumping increases, the viability of the aquifer, and of the surrounding ecosystems and agricultural economy are placed at serious risk.

6.2.2.4 The agricultural sub-model

This sub-model (Figure 2b) allows the full potential of SDM to be explored. By changing any parameter, the value for agricultural demand will change according to the feedback relationships in the model. Unlike the other demands, this is not a pre-defined time-series. Water use is calculated for each timestep based on the sub-model relationships and the initial values for parameters such as the monthly tariff increase. In addition to water demand, revenue generated from water sales can also be output from this sub-model. In this sub-model, the parameters that were changed during these tests are:

1. the value for the annual agricultural water demand change (baseline = -0.014881% per month - equivalent to 5% reduction over 28 years (Chahed et al., 2008)). This was changed by factors of 0.5 and 2, i.e. halved and doubled respectively.
2. the value for the proportion of revenue invested in efficient irrigation (baseline = 10%). This was changed by factors of 0.5 and 2.
3. the annual tariff increase (baseline = 1.25% per month or 15% per year (Chenini et al., 2003). This was changed by factors of 0.5 and 2.
4. the amount of water saving possible by implementing water saving measures (baseline = 20%. Estimated value). This was changed by factors of 0.5 and 2.
5. the change to global food prices (baseline = 0.9416% per month based on 11.3% average annual change from 2000-2012. fao.org). This was changed by factors of 0.5 and 2.

All ten tests had negligible impact on the overall Kairouan water balance (Figure 8a). The range of average annual Kairouan deficit under all scenarios is from 9.5 x 10^6 m^3 yr^{-1} (doubling the amount of revenue invested for efficient irrigation) to 11.6 x 10^6 m^3 yr^{-1} (doubling the global food price increase rate). None of the changes led to a significant improvement in the current situation. Figure 8b, which shows how the revenue generated changed in these tests, suggests that a trade-off must be made between increasing the revenue generated and at the same time to decrease the amount of water use to protect the aquifer water quantity and quality, ecosystem services and agricultural viability in the region (e.g. while doubling the food price increase rate offers a better revenue, it also leads to greater overexploitation of the Kairouan aquifer, Figure 8).

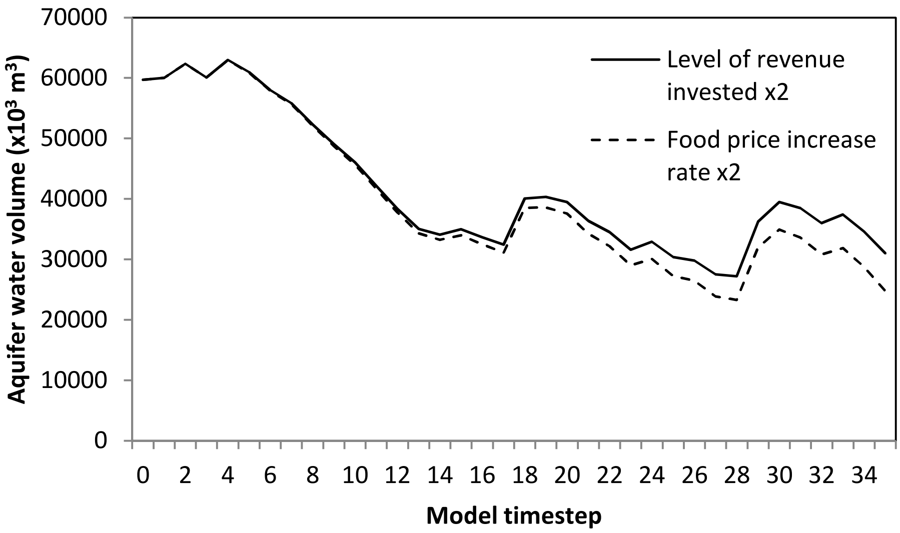

Figure 8a: Aquifer water trends produced from doubling the level of investment and doubling the global food price increase rate. The results from all other tests in Section 6.2.2.4 fall between these trends.

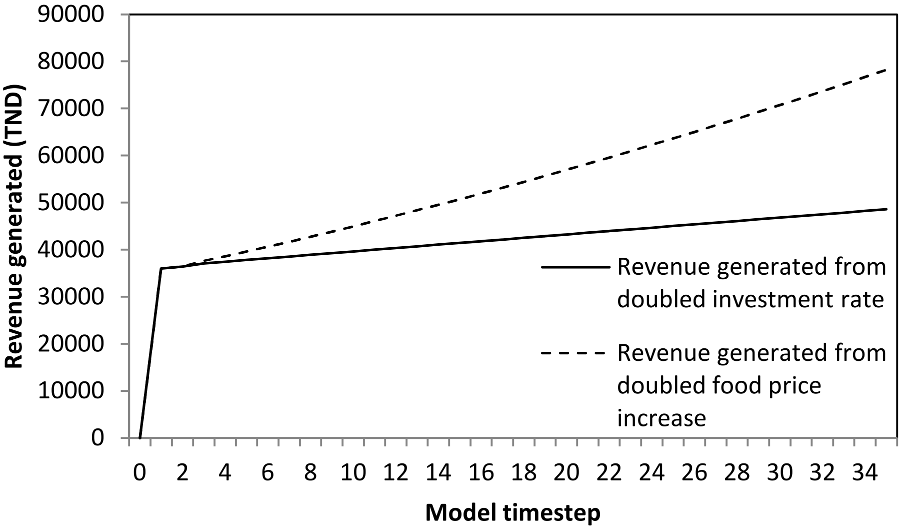

Figure 8b: Simulated revenue generated for the tests that doubled the level of investment and the global food price increase rate. The trends show different responses, with a doubling of the food price increase rate leading to a much greater level of revenue generated by the end of the simulation. The results from all other tests in Section 6.2.2.4 fall between these trends.

7. Discussion

Both modelling approaches indicate that at present, Kairouan aquifer is undergoing depletion. OOBN modelling showed greater depletion than SDM, with both approaches showing deficit lower than estimations from rudimentary mass balance calculations (Luc, 2005), but are consistent with the pattern of decline observed by Le Goulven et al. (2009). Hypothetical water management scenarios allowed a more thorough comparison of the two methods.

Both approaches use a sensitivity-type approach to the scenarios - changing one value and observing the effects. However, how these approaches were carried out, and the merits and limitations of each are different. In the OOBN framework, the hypothetical scenarios consisted of minimising or maximising key model parameters. In addition, an objective function was set such that the goal was to minimise or maximise the water volume stored in the aquifer (within the constraints of the CPTs). The influencing parameters were altered by the model in order to achieve this objective. The main observed impacts were to the amount of infiltration recharge on the supply side and the volume of pumping to the coast on the demand side. The interpretation is that if the aquifer were to undergo recharge, it is one of these two parameters that would be most likely to be affecting this change, either together or independently. In terms of policy interventions (governance), very little can realistically be done to impact significantly on natural water supply, however the volume of water pumping could be influenced. Setting objective functions to observe how influencing parameters respond is not available within the SDM environment, and represents an important difference between the two methods. OOBN modelling, through the use of CPTs, generates probabilistic results, which may give the end user a better handle on the uncertainties associated with a result set. However, these probabilities, while useful, are constrained by the data on which they are based. It still represents an advantage over SDM, where the results are usually, though not always, deterministic (although stochastic SDMs have been developed, Mosekilde and Rasmussen, 1983). OOBN indicated that changes to the volumes pumped to the coast hold the greatest promise for aquifer rehabilitation.

In the SDM framework, for the 'simple' parameters (e.g. rainfall and industrial and domestic demand), these were scaled by various factors (Section 6.2.2) relative to the baseline and resulted in linear model response. SDM allowed for the testing of the more complex feedback-driven agricultural water demand sub-model. The agricultural demand sub-model aimed to represent to full utility of SDM and provide a strong contrast with OOBN modelling. For the more complex agricultural sub-model, while key parameters were still scaled in a sensitivity-type approach, the role of the feedback structure, including non-linear relationships linking some of the variables, meant that the response in agricultural water demand to these changes was not linearly related to the scaling factor, nor was the ultimate aquifer response. Positive (i.e. reinforcing) and negative (i.e. self-stabilising) loops are incorporated. Many parameters depend on values from previous time steps. The feedback representation in SDM is not available in OOBN due to the inherent acyclic nature of this approach. It was expected that changing parameter values in this sub-model would lead to substantial changes in demand. However, this was not the case (Section 6.2.2.4). All model results except for one (doubling the global food price increase) were within 10% of each other.

Based on the interconnected feedback loops simulating agricultural water demand (Figure 2b) the behaviour of this factor is more complex: Any change in demand, ΔD, is subtracted from the previous agricultural water demand value, while a decrease in demand decreases the revenue generated. This, consequently, leads to decreases in the amount of revenue invested for efficient irrigation practices and for regulation and enforcement of water laws. Because both of these values will be lower than in the previous time step, the subsequent effect from the water savings parameter produces no changes on water demand at the next time step. By contrast, the effect from the regulation parameter (governance/policy) is to decrease water demand, as farmers move towards private (unregulated) irrigation from the public (monitored) system. The lower level of enforcement is assumed to encourage farmers to illegally take water as they are more under pressure from the higher tariff and less under pressure from strict regulation enforcement. Additionally a slight, constant, decrease in agricultural demand at each time step is imposed.

Finally, there is an increase in demand due to the influence of rising global food prices. The impact of these interactions is a net decrease in total agricultural water demand, but the level of decrease is lower than expected from changing the tariff alone. This, in turn, suggests that raising tariffs in order to lower demand, or changing the proportion of revenue invested to promote efficient irrigation, may not be as effective as hoped. These interactions are in no way exhaustive regarding the socio-economic and governance factors influencing agricultural eater demand; there may be other interactions at work that are neglected in this (rather simplified) sub-model. They are, however, sufficient for giving a clear trend of the complexity and the issues at hand for the region and the potential of SDM to explore them.

Agriculture is by far the largest employer and the largest economy in the region. It is unlikely that a policy would be put in place that would threaten this socio-economic driver. Policies for promoting the growth of less water-intensive crops or improving irrigation efficiency are likely to be preferred. It is unclear how these socio-economic factors will impact on agricultural water demand, and how effective they will be, especially under future climate change scenarios, but the model indicates that they will be critical in determining future agricultural water use, as well as being a useful (decision maker's) tool for the qualitative and quantitative assessment of the impacts of different policies.

Both approaches suggest that transferring water from the aquifer to coastal cities has a large impact on Kairouan aquifer water volumes. OOBN modelling suggested that significant improvement or worsening of the water deficit can occur depending on whether the pumped volume is minimised or maximised (within the constraints of the CPTs) respectively. However, while the OOBN approach is constrained by the limits of the CPTs, the SDM approach is not. Here, coastal pumping was scaled between 0.6 and 1.4 times the baseline values, but could have been scaled to any value. As with the OOBN results, significant impacts in aquifer response were observed. Both approaches suggest that reductions in the volume pumped out to coastal cities offers the best realistic option for reducing the over-exploitation in the future and also for preserving the sensitive nearby sebkha regions and local water quality. By maintaining Kairouan aquifer water volumes, the agricultural economy of the region could also be sustained. Despite this, due to the current situation it is suggested that efforts should also be made to reduce domestic consumption (e.g. through subsidies for water-saving measures or a tariff increase), and to restrain industrial consumptive growth (e.g. through tariff or abstraction controls).

This study has highlighted the advantages and limitations of both modelling approaches. While OOBN modelling is ideally suited to generating results that can incorporate and account for uncertainty in input data, giving probability distributions as output, and can set objective functions to observe the corresponding impacts on influencing variables, it is an acyclic modelling paradigm preventing its use in assessing complex feedback-driven systems. It is in the simulation of non-linear feedback processes that SDM excels, helping to deepen understanding of how a system operates and of how feedbacks may result in consequences differing to those intended. Additionally, OOBN is unable to handle time series data, unlike SDM.

This study suggests that in some cases, using both methods to complement each other in the evaluation of water resources can add depth and insight to the results produced. By using these approaches together, instead of considering them in isolation, a more robust systems analysis may be undertaken that can lead to better informed policy decisions, the conclusion being that exploiting the merits of both methods is better than choosing between them; they are complementary rather than rival methodologies. In the context of this study, this means using both approaches to better understand the impacts of potentially implemented policy options aimed at securing the regional water resource and the associated uncertainty. Those options that are likely to have the most favourable impact on water quantity and quality, ecosystem conservation and the development of the agricultural economy can be fully assessed, leading to better informed decision making.

8. Conclusions

This paper describes the use of two different modelling approaches, System Dynamics Modelling and Object-Oriented Bayesian Network Modelling for simulation of the same groundwater system. The volume of water in the Kairouan aquifer, Tunisia was the main parameter being studied. Both models were in good agreement when the baseline dataset was used, indicating current overexploitation of the aquifer. A number of hypothetical management scenarios were tested. The results from the two approaches agreed that only changing the volume of water pumped to coastal cities has a significant impact on aquifer water volumes, and reductions offer the best solution for aquifer rehabilitation and an end to overexploitation.

The main aim was to compare and contrast the modelling paradigms. The model implementations and discussion showed that each approach has its own advantages and disadvantages. It is shown that OOBN modelling is well suited to modelling systems where the parameters are uncertain, and where the uncertainty can be quantified as a probability distribution. It also allows for probabilistic model outputs, giving policy makers a better handle on uncertainties associated with predictions, though the probabilities generated are constrained by the data used in the model. OOBNs are particularly useful for examining what impact fixing an objective function to a given value has on influencing inputs and outputs. This means for example that should a minimum aquifer volume be set, those parameters most important to affecting this limit could be identified, lending focus to potential policy decisions.

System Dynamics is used to investigate the behaviour of complex systems which are governed by feedback and non-linearity, something which may not be done using OOBNs due to their acyclic nature. Unintended, and sometimes counter-intuitive system behaviour might be uncovered that was not predictable beforehand. A feedback-driven agricultural sub-model was built in order to highlight to utility of SDM and to show the contrast with OOBN. It was shown for example, that doubling one parameter did not result in as much lowering of the water demand as might have been intended as a result of the competing actions of the various feedback loops.

It is suggested that in some cases, rather than using these approaches in isolation, coupling the methods and using one to complement the other may add significant value to the outcomes of a study as opposed to if only one approach was adopted. For example, OOBNs modelling can provide a better understanding of uncertainty in inputs and outputs, while SDM can shed light on the complex, non-linear response of a system to alterations in various initial states. The modeller should think carefully about which approach to adopt, and should not rule out using both to complement each other.

Finally, the combined use of SDM and OOBN may provide an improved insight leading to better informed decision makers. For instance, in this study it was shown that significant changes to the annual tariff increase did not lower the agricultural water demand as much as expected because of the other feedback processes acting within this sub-model, while OOBN modelling indicated that if minimum aquifer volumes were required by policy, then the biggest impact would most likely be forced upon the water pumped to the coast, which would have to decrease in volume to meet the requirement. By combining the two approaches, better informed decisions based on deeper systems understanding can be made, and decisions which may unintentionally prove detrimental long term water resources management can be avoided.

Acknowledgements

For work presented here for SDM was partially funded by the EU FP7 project WASSERMed (European Framework Project Number 244255, www.wassermed.eu). JS, LVL, ZK and DS also acknowledge the sharing of data and information from other WASSERMed partners, particularly INAT (Institut National Agronomique de Tunisie) (especially Zohra Lili-Chabaane, Hedia Chakroun and Ines Oueslati) and IRD (Institut pour la Recherche et le Développement), Montpellier, France (especially Christian Leduc and Andrew Ogilvie). They also thank the Centro Euro-Mediterraneo per i Cambiamenti Climatici (CMCC), Italy for the forecast of rainfall.

JLM acknowledges the contributions of the following people and organizations: Dr. Tony Jakeman from the Integrated Catchment Assessment and Management Centre (iCAM), for their help and support in this research line. On the other hand, the study for OOBN has been partially supported by the European Community 7th Framework Project GENESIS (226536) on groundwater systems and from the subprogram Juan de la Cierva (2010) of the Spanish Ministry of Science and Innovation as well as from the Plan Nacional I+D+i 2008–2011 of the Spanish Ministry of Science and Innovation (subprojects CGL2009- 13238-C02-01 and CGL2009-13238-C02-02).

We also thank two anonymous reviewers for useful comments and suggestions on an earlier version of this manuscript.

7. References

Ahmad, S., Simonovic, S.P., 2000. System Dynamics Modelling of reservoir operations for flood management. Journal of Computing in Civil Engineering. 14(3), 190-198.

Arnell, N.W., Livermore, M.J.L., Kovats, S., Levy, P.E., Nicholls, R., Parry, M.L., Gaffin, S.R., 2004. Climate and socio-economic scenarios for global-scale climate change impact assessments: characterising the SRES storylines. Global Environmental Change. 14, 3-20.

Barlas, Y., 2002. System dynamics: systemic feedback modelling for policy analysis in knowledge for sustainable development – an insight into the encyclopaedia of life support. UNESCO; Eoloss, Paris, France; Oxford, UK.

Bayes, T., 1991. An essay towards solving a problem in the doctrine of chances. Bayesian Statistics: Principles, Models, and Applications. 189-215.

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, 219–239.

Bromley, J., Jackson, N., Clymer, O., Giacomello, A., Jensen, F., 2005. The use of Hugin to develop Bayesian Network as an aid to integrated water resource planning. Environmental Modelling & Software. 20, 231–242.

Cain, J., 2001. Planning Improvements in Natural Resources Management. Centre for Ecology and Hydrology, Wallingford, UK.

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

Chahed, J., Hamdane, A., Besbes, M., 2008. A comprehensive water balance of Tunisia: Blue water, green water, virtual water. Water International. 33, 415-424.

Chenini, F., Huibers, F.P., Agodzo, S.K., van Lier, J.B., Duran, A., 2003. Use of wastewater in irrigated agriculture. Country studies from Bolivia, Ghana and Tunisia. Volume 3: Tunisia. Wageningen, WUR. ISBN: 90-6754-703-4

Chung, G., Lansey, K., Blowers, P., Brooks, P., W., E., Stewart, S., Wilson, P., 2008. A general water supply planning model: Evaluation of decentralized treatment. Environmental Modelling & Software. 23, 893-905.

Falkenmark, M., Molden, D., 2008. Wake up to realities of river basin closure. International Journal of Water Resource Development. 24, 201-215.

Farmani, R., Jørgen Henriksen, H., Savic, D., 2009. An evolutionary Bayesian belief network methodology for optimum management of groundwater contamination. Environmental Modelling & Software. 24 (3), 303–310.

Farmani, R., Henriksen, HJ., Savic D., 2009. An evolutionary Bayesian belief network methodology for optimum management of groundwater contamination. Environmental Modelling and Software. 24,303–310.

Ford, A., 1999. Modelling the Environment: An Introduction to System Dynamics Modeling of Environmental Systems. Island Press, Washington, D.C., U.S.A.

Forrester, J., 1961. Industrial Dynamics. Pegasus Communications, Waltham, MA, U.S.A.

Haraldsson, H.V., Sverdrup, H.U., 2004. Finding simplicity in Complexity in Biogeochemical modelling, In: In Wainwright J. and Mulligan M. (eds.) (Ed.), Environmental Modelling: Finding Simplicity in Complexity. John Wiley and Sons, Ltd.: West Sussex, England, UK, pp. 211-223.

Henriksen, H.J., Barlebo, H.C., 2007. Reflections on the use of Bayesian networks for adaptive management. Journal of Environmental Management. doi:10.1016/ j.jenvman.2007.05.009.

Henriksen, H.J., Rasmussen, P., Bandt, G., von Bulow, D., Jensen, F.V., 2007. Public participation modelling using Bayesian networks in management of groundwater contamination. Environmental Modelling and Software. 22, 1101-1113.

Jensen, F.V., 1996. An Introduction to Bayesian Networks. UCL Press, London.

Jensen, F.V., 2001. Bayesian Network and Decision Graphs. Department of Computer Science, Aalborg University, Aalborg, Denmark.

Khan, S., Yufeng, L., A., A., 2009. Analysing complex behaviour of hydrological systems through a system dynamics approach. Environmental Modelling and Software. 24, 1363-1372.

Kojiri, T., Hori, T., Nakatsuka, J., Chong, T.-S., 2008. World continental modelling for water resources using system dynamics. Physics and Chemistry of the Earth. 33, 304-311.

Le Goulven, P., Leduc, C., Salah Bachta, M., Poussin, J-C., 2009. Sharing scarce resources in a Mediterranean river basin: Wadi Merguellil in central Tunisia. River Basin Trajectories: Societies, Environments, and Development. pp. 147-170.

Leduc, C., Ben Ammar, S., Favreau, G., Beji, R., Virrion, R., Lacombe, G., Tarhouni, J., Aouadi, C., Zenati Chelli, B., Jebnoun, N., Oi, M., Michelot, J.L., Zouari, K., 2007. Impacts of hydrological changes in the Mediterranean zone: envrionmental modifications and rural development in the Merguellil catchment, central Tunisia. Hydrological Sciences Journal. 52, 1162-1178.

Li, L., Simonovic, S., 2002. System dynamics model for predicting floods from snowmelt in North American prairie watersheds. Hydrological Processes. 16, 2645-2666.

Little, L.R., Kuikka, S., Punt, A.E., Pantus, F., Davies, C.R., Mapstone, B.D., 2004. Information flow among fishing vessels modelled using a Bayesian network. Environment Modelling Software. 19, 27–34.

Lipsey, R.G., Chrystal, K.A., 1999. Principles of Economics. 9th ed. New York (USA): Oxford University Press.

Luc, J.P., 2005. Blue and green water accounting: The Merguellil River basin, Report for the Comprehensive Assessment of Water Management in Agriculture. International Water Management Institute. p. 78.

Malekmohammadi, B., Kerachian, R., Zahraie, B., 2009. Developing monthly operating rules for a cascade system of reservoirs: application of Bayesian Networks. Environmental Modelling & Software. 24 (12), 1420–1432.

Martín de Santa Olalla, F.J., Domı´nguez, A., Ortega, J.F., Artigao, A., Fabeiro, C., 2006. Bayesian networks in planning a large aquifer in Eastern Mancha, Spain. Environmental Modelling and Software. 22, 1089–1100.

Martinez-Santos, P., Henriksen, H.J., Zorrilla, P., Martinez-Alfaro, P.E., 2010. Comparative reflections on the use of modelling tools in conflictive water management settings: The Mancha Occidental aquifer, Spain. Environmental Modelling and Software. 25, 1439-1449.

Mazzoleni, S., Rego, F., Giannino, F., Legg, C., 2004. Ecosystem Modelling: Vegetation and disturbance, In: In Wainwright J. & Mulligan M. (eds.) (Ed.), Environmental Modelling: Finding Simplicity in Complexity. John Wiley and Sons Ltd.: West Sussex, England, UK, pp. pp 171-186.

Meadows, DH., Meadows, DL., Randers, J., Behrens III, WW., 1972. The Limits to Growth. Universe Books, New York. 205 pp.

Molina, JL., Bromley, J., García-Aróstegui, JL., Sullivan, C., Benavente, J., 2010. Integrated water resources management of overexploited hydrogeological systems using Object-Oriented Bayesian Networks. Environmental Modelling and Software. 25,383–397.

Molina, JL., Jakeman, AJ., 2011. A Dynamic Bayesian Network Modelling Approach for Integrated Water Resources Management. p 887. 8th IWA Symposium on Systems Analysis and Integrated Assessment, WATERMATEX 2011

Molina, JL., Farmani, R., Bromley, J., 2011. Aquifers Management through Evolutionary Bayesian Networks: The Altiplano Case Study (SE Spain). Water Resources Management. DOI 10.1007/s11269-011-9893-z

Morteza Mesbah, S., Kerachian, R., Reza Nikoo, M., 2009. Developing real time operating rules for trading discharge permits in rivers: application of Bayesian Networks. Environmental Modelling & Software. 24 (2), 238–246.

Mosekilde, E., Rasmussen, S., 1983. Random processes in dynamics systems. Dynamica. 9 (1), 33-39

Muetzelfeldt, R., 2010. Extended System Dynamics modelling of the impacts of food system drivers on food security, livelihoods and the environment, Report for the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), p. 27pp.

Muetzelfeldt, R., Massheder, J., 2003. The Simile visual modelling environment. European Journal of Agronomy. 18, 345-358.

Mulligan, M., Wainwright, J., 2004. Modelling and Model Building., In: In Wainwright J. & Mulligan M. (eds.) (Ed.), Environmental Modelling: Finding Simplicity in Complexity: West Sussex, England, UK, pp. 7-73.

Ordóñez Galán, C., Matías, J.M., Rivas, T., Bastante, F.G., 2009. Reforestation planning using Bayesian Networks. Environmental Modelling & Software. 24 (11), 1285–1292.

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems. Morgan Kaufmann, San Mateo, CA.

Ribarova, I., Assimacopoulos, D., Jeffrey, P., Daniell, K., Inman, D., Vamvakeridou-Lyroudia, L.S., Melin, T., Kalinkov, P., Ferrand, N., Tarnacki, K., 2011. Research-supported participatory planning for water stress mitigation. Journal of Environmental Planning & Management. 54, 283-300.

Ross, A., Martinez-Santos, P., 2010. The challenge of groundwater governance: case studies from Spain and Australia. Regional Environmental Change. 10, 299-310.

Simonovic, S., 2002. World water dynamics: global modelling of water resources. Journal of Environmental Modelling. 66, 249-267.

Stave, K.A., 2003. A system dynamics model to facilitate public understanding of water management options in Las Vegas, Nevada. Journal of Environmental Management 67 303-313.

Sterman, J.D., 2000. Business Dynamics, Systems Thinking and Modeling for a Complex World. Irwin/ McGraw-Hill, New York, U.S.A.

Sušnik, J., Vamvakeridou-Lyroudia, L.S., Savic, D., Kapelan, Z., 2011a. System Dynamics Modelling applied for the integrated simulation of complex water systems, Proceedings of the 8th IWA Symposium on Systems Analysis and Integrated Assessment, 20-22 June 2011: San Sebastian, Spain, pp. 535-542.

Sušnik, J., Vamvakeridou-Lyroudia, L.S., Savić, D.A., Kapelan, Z., 2011b. Evaluating water-related security threats for complex water systems using System Dynamics Modelling, Proceedings of the 11th International Conference on Computing and Control in the Water Industry: University of Exeter, Exeter, UK, pp. 71-76.

Sušnik, J., Vamvakeridou-Lyroudia, L.S., Savić, D.A., Kapelan, Z., 2012. Integrated System Dynamics Modelling for water scarcity assessment: case study of the Kairouan region, Accepted for publication in the Science of the Total Environment.

Ticehurst, J.L., Newham, L.H.T., Rissik, D., Letcher, R.A., Jakeman, A.J., 2007. Bayesian network approach for assessing the sustainability of Coastal Lakes in New SouthWales, Australia. Environment Modelling and Software. 22 (8), 1129–1139.

Tidwell, V.C., Passell, H.D., Conrad, S.H., Thomas, R.P., 2004. System dynamics modeling for community-based water planning: Application to the Middle Rio Grande. Aquatic Sciences. 66, 357-372.

Vamvakeridou-Lyroudia L.S., Leduc C. and Savic D.A. 2008. System Dynamics Modelling: The Merguellil valley water system, Report No.2008/04, Centre for Water Systems, School of Engineering, Computing and Mathematics, University of Exeter, Exeter, U.K., 98p, (accessible at www.ex.ac.uk/cws).

Vamvakeridou-Lyroudia, L.S., Inman, D., Ribarova, I., and Savić, D.A. 2009. Modelling water saving in the upper Iskar region, Proc. 10th Int. Conf. on Computing and Control for the Water Industry CCWI 2009, 1-3 Sept. 2009 University of Sheffield, UK, 767-773

Varis, O., Kuikka, S., 1999. Learning Bayesian decision analysis by doing: lessons from environmental and natural resources management. Ecological Modelling. 119, 177–195.

Varis, O., Fraboulet-Jussila, S., 2002. Water resources development in the Lower Senegal River Basin: conflicting interests, environmental concerns and policy options. Journal of Water Resources Development. 18, 245–260

World Water Assessment Programme. 2009. The United Nations World Water Development Report 3: Water in a Changing World. Paris: UNESCO, and London: Earthscan.