STRATEGIES TO COMBAT SALT WATER INTRUSION IN COASTAL AQUIFERS – A MODEL-BASED EXPLORATORY ANALYSIS

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Abstract
Coastal communities dependent upon groundwater resources for drinking water and irrigation are vulnerable to salinization of the groundwater reserve. The increasing uncertainty associated with changing climatic conditions, population and economic development, and technological advances in agriculture, water treatment, and water purification, poses significant challenges for freshwater management. The research reported in this paper offers an approach for investigating and addressing the challenges to freshwater management using innovative exploratory modeling techniques. We present a generic systems model of a low lying coastal region that depends on its groundwater resources. This systems model covers population, agriculture, industry, and the groundwater reserve. The model captures the key dynamics of these subsystems and their interactions (adapted from Hoekstra, 1998). The systems model in turn is coupled to a powerful scenario generator, which is capable of producing a comprehensive range of plausible future scenarios (Lempert et al., 2003). Each scenario describes a unique future pathway of the evolution of population, the economy, agricultural and water purification technologies. We explore the behavior of the systems model across the wide range of scenarios and analyze the implications of these scenarios for freshwater management in the coastal region. In particular, the results are summarized in a decision tree that provides insights into the expected outcomes given the various uncertainties, thus supporting the development of effective policies for managing the coastal aquifer.

1 INTRODUCTION
Many coastal regions in the world are subject to seawater intrusion in aquifers resulting in severe deterioration of the quality of the groundwater resources (Narayan et al. 2003). Indeed, saltwater intrusion as a result of groundwater over-exploitation is a major concern in many aquifers throughout Europe (EEA 1999), America (Barlow 2003, NRC 2011), Australia (Narayan et al 2003) and the developing world (Sales 2008). In its fourth assessment report the IPCC includes the following major projected impacts as examples of the possible effects of climate change due to changes in extreme weather and climate events: decreased freshwater availability due to saltwater intrusion, salinization of irrigation water, water shortages for settlements, industry and societies, potential for population migration, land degradation, lower yields/crop damage and failure, amongst others (IPCC 2007). Each of these potential impacts may affect coastal communities with low per capita income who are dependent upon groundwater resources for drinking water and agricultural purposes (Sales 2008, NRC 2011), making them particularly vulnerable.

Despite our current understanding that these communities are vulnerable to becoming climate refugees, few analytical tools for studying the interrelationships between the factors influencing human migration, and the land and water use practices of the coastal communities dependent upon aquifers are available. In this paper, we seek to address this gap first by developing a simple yet generic model of a coastal community dependent upon its groundwater resources. This systems model (adapted from Hoekstra, 1998) covers population, land use including agriculture, and the groundwater reserve. The model captures the key dynamics of the subsystems and their interactions. The systems model, in turn, is coupled to a powerful scenario generator, which is capable of producing a comprehensive range of plausible future scenarios (Lempert et al., 2003). We explore the behavior of the systems model across the wide range of scenarios and analyze the implications of scenarios of climatic conditions, population growth and land use policy for freshwater management in the coastal region. We conclude that irrespective of the scenarios, the modeled system is likely to deteriorate, both in terms of the population that can be sustained by the region and in terms of the amount of salt in the aquifer. Next research steps, aimed at designing effective strategies for managing the aquifer are shortly discussed.

2 A MODEL OF SALINIZATION IN A SEMI-ARID COASTAL AGRICULTURAL COMMUNITY

2.1 Conceptual description of the model

We adopt a single layer approach to modeling a coastal aquifer and conceptualize the sand/gravel aquifer as a single hydrostratigraphic unit, bounded at the base by impermeable bedrock of negligible gradient. According to Narayan et al.(2003), the assumption of uniformity of the aquifer is defensible even for coastal aquifers with laterally discontinuous strata that exhibit vertical connections between sandy units. In common with Kooi and Groen (2000), the aquifer is conceptualized as unconfined at the upper boundary representing the unconsolidated nature of the sediments of many alluvial coasts.

A cross-sectional vertical slice through the aquifer is depicted in Figure 1 (from Barlow 2003), with the groundwater source entering from the left and the hydrostatic pressure of the seawater present on the right. When the aquifer is fully charged with freshwater it extends 100m in length and contains a volume of 1,8 x 10^6 m^3.

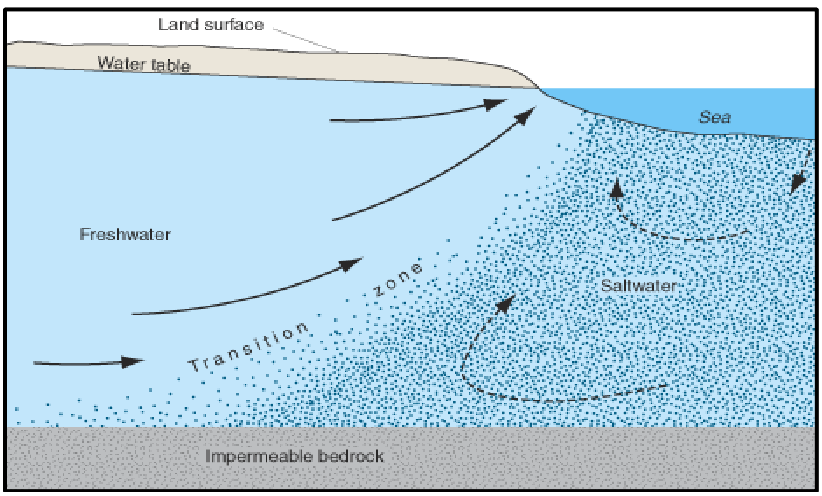

Figure 1: Cross-section through a uniform sand aquifer indicating the fresh groundwater resource on the left, the sea water on the right and the halocline forming the interface or transition zone between the two water bodies (from Barlow 2003).

In contrast to many groundwater models (Kooi & Groen 2000, Narayan 2003, Barlow 2003), we include the population and land-use dynamics of the coastal community as well as water management practices in our model. In short, we treat the coastal community and its aquifer as a social-ecological system and build a finite difference equation model according to the system dynamics modeling method (Meadows 1985). This means that we are able to cross disciplinary boundaries and investigate the effects of climate change and land and water-use rules on the interlocking social and resource-based sub-systems. Outcomes of interest to this investigation are the time evolution of the water and food shortages, as these are indicative of the potential migratory response of climate refugees (see Figure 2).

The data used in calibrating and running the coastal community aquifer model are based on field investigations from Hoekstra (1998) subsequently adapted for teaching purposes to reveal a full range of dynamic behavior (see Slinger 2011, Slinger et al. 2010).

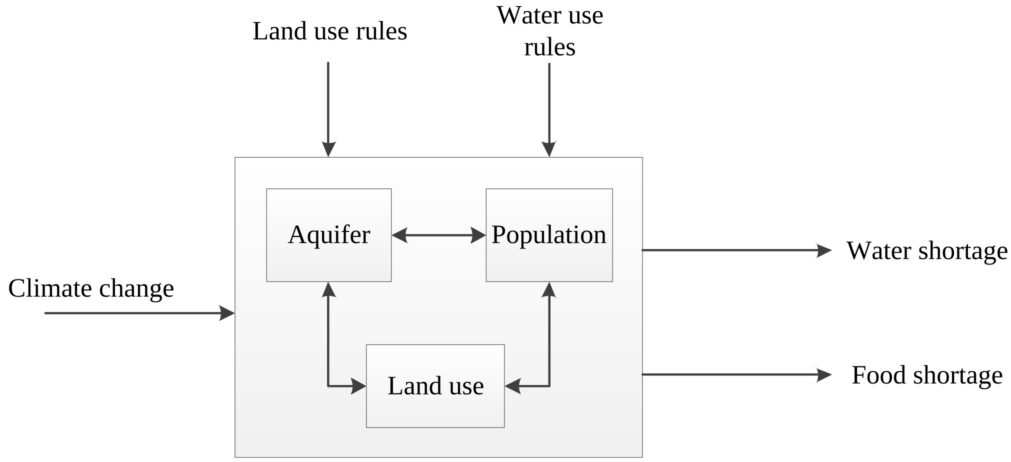

Figure 2: Conceptual diagram of coastal communities dependence on ground water resources

2.2 Detailed model specification

The coastal community aquifer model (CCA) comprises six sub-sections, namely: a population section, an aquifer (quantity and quality) section, a land-use section and a water use section. In the population section, the birth, death and emigration rates are modeled as dependent on the number of people making up the coastal community. This is described in the following equations.

$$\frac{d}{dt}x_1 = x_{11} - x_{12} - x_{13}$$

where x_1 is the population, $x_{11}$is the birth rate, $x_{12}$is the death rate, and $x_{13}$is the emigration rate. The birth rate in turn depends on the population, the normal birth rate (bn) and a non-linear function indicating the trend in the average birth rate over time. The people living along the coast are modeled as migrating in response to shortages in food and water in accordance with observed and predicted responses to environmental stresses (IPCC 2007, Sales 2008, NRC 2011). Those that stay may be forced to drink water of a quality lower than the standards prescribed for drinking water by the World Health Organisation (EEA 1999). The death rate is formulated as depending on the product of the death normal (dn) and a non-linear function $\left(df(x_3)\right)$ indicating the influence of the chloride content of the water on the death rate. The emigration rate depends on the emigration normal (emn) and the independent effects of water and food shortages on emigration ($emf_1(short_{water})$) and $emf_2(short_{food})$).

$$x_{11} = x_1.bn.bf(t)$$
$$x_{12} = -x_1.dn.df(x_3)$$
$$x_{13} = -x_1.emn.emf_1(short_{water}).emf_2(short_{food})$$

Although the people of the agriculturally-dependent coastal community are primarily employed in the agricultural sector, a small percentage is employed in the industrial sector ($\%ind$).

THE AQUIFER

The volume of freshwater in the aquifer (x_2) is influenced by is the replenishment by rainwater x_{21}, the replenishment by a remote riverine source (x_{22}), the irrigation return flow (x_{23}) and by the extraction of freshwater by the coastal community (x_{24}). Whereas the replenishment by rainfall is dependent on the land area ($area$) and a time dependent rainfall function ($rainf(t)$), a certain proportion (irn) of the water used in irrigation (irr) filters down into the aquifer (Narayan et al. 2003, Barlow 2003). The extraction of freshwater occurs in response to the demand for domestic water ($demand_{domestic}$) water for industry ($demand_{industrial}$) and water for agriculture ($demand_{agriculture}$). Unfortunately, the total demand cannot always be met. The degree to which the demand is met is determined by formal water management agreements. In the model, these agreements are specified in terms of the length of the aquifer (*l*), which is directly related to the volume of freshwater present in the aquifer.

$$\frac{d}{dt}x_2 = x_{21} + x_{22} + x_{23} - x_{24}$$
$$x_{21} = area.rainf(t)$$
$$x_{22} = riverf(t)$$
$$x_{22} = irr.irn$$
$$x_{24} = \left(demand_{domestic} + demand_{industrial} + demand_{agriculture}\right).extrf(l(x_2))$$

The amount of salt diffusing across the seawater-freshwater halocline that bounds the seaward extent of the aquifer per unit time (x_{31}) is directly proportional to the cross-sectional area at the interface ($area_{cross}$). However, the diffusion rate per unit area varies according to the length of the aquifer. When the aquifer extends to its full length, the diffusion rate per unit area is about 0,7 of the nominal diffusion constant ($difn$). When the aquifer reduces to below 40% of its length, the diffusion rate per unit area increase to 1,6 times the diffusion constant. As the aquifer empties this rate even approaches 1,75 times the diffusion constant. This non-linear behavior is captured in the diffusion function ($dif(l(x_1))$) which reflects the enhanced diffusion of salt owing to the increased hydrostatic pressure from the seawater associated with reduced freshwater. The diffusion process is responsible for the salinization of the freshwater aquifer (Barlow 2003, Narayan et al 2003), an effect additional to the landward intrusion of seawater that accompanies the reduction in the volume of freshwater (Kooi & Groen 2000). A further source of salt to the aquifer is provided by the seepage of salt from agricultural return flow (x_{32}) (Narayan et al. 2003). This is represented as a third order exponential material delay (Kirkwood 1998) with a delay time of 6 years. Finally, salt is removed from the aquifer when water is pumped out. The salt present in the aquifer is assumed to be distributed uniformly, so that the salt removed by extraction (x_{33}) is given by the product of the extraction rate of freshwater (x_{24}) and the average concentration of salt in the aquifer (${}^{x_2}/_{x_3}$).

$$\frac{d}{dt}x_3 = x_{31} + x_{32} - x_{33}$$
$$x_{31} = area_{cross}.difn.dif(l(x_2))$$
$$x_{32} = DELAY(x_{22}, 6\,yr)$$
$$x_{33} = x_{24}.{}^{x_2}/_{x_3}$$

LAND USE

The available land area is utilized for the functions of infrastructure, nature areas, housing, industry and agriculture. The percentage of land area allocated to infrastructure and nature is assumed constant. However, as the community grows, the area occupied by housing and industry will grow at the expense of agricultural land. This housing and industrial area growth rates ($x_{41}$and x_{42}, respectively) are modeled by comparing the demand of people for housing and industrial area with the existing housing and industrial areas. The required housing area is determined by first determining the number of houses required and then multiplying this by the average area per house ($area_{house}$). The number of houses required is the quotient of the population and the average number of people per household (*pph*). The required industrial area is determined by first calculating the number of people working in industry and then multiplying by the area required per worker ($area_{worker}$). If the required areas are less than the existing area of houses and industry, no changes are made. If the required housing area exceeds that allocated to houses, then the difference between the required area and the actual area is eliminated over a period of years (adj). In effect, if this period is 5 years this means that one fifth of the housing area shortage is supplied annually. A similar approach is adopted for industrial land with a percentage of the industrial land shortage being supplied on an annual basis.

$$\frac{d}{dt}x_4 = -x_{41} - x_{42}$$
$$\frac{d}{dt}x_5 = x_{41}$$
$$\frac{d}{dt}x_6 = x_{42}$$
$$x_{41} = \left({}^{x_1}\!/_{pph} . area_{house} - x_5 \right)/adj \text{ if } {}^{x_1}\!/_{pph} . area_{house} > x_5 \text{ and 0 otherwise}$$
$$x_{42} = \left(x_1 . \%ind. area_{worker} - x_6 \right)/adj \text{ if } x_1 . \%ind. area_{worker} > x_6 \text{ and 0 otherwise}$$

The land not in use for housing and industry is available to agriculture. The agricultural land use can be divided into irrigated lands (x_7) and rain-fed or non-irrigated lands (x_8) (Saysel et al. 2002). The rate at which the conversion to agricultural land occurs differs for irrigated (x_{71}) and non-irrigated land (x_{81}), with a higher percentage generally going to irrigated land (ad_{71}) than to non-irrigated land (ad_{81}). As the demand for housing and industrial land increases (in response to increasing population) and exceeds the stock of available land, the land available to agriculture declines and agricultural land has to be converted to urban area. The rates at which the irrigated and non-irrigated land become available for urban usage (x_{72} and x_{82}, respectively) depend on the land area required for urban development and the fraction of agricultural land irrigated or not irrigated.

Another land conversion mechanism is also at work. The irrigated land can only be sustained when there is sufficient water to irrigate (Saysel et al 2002, Saysel & Barlas 2001). The product of the minimum water demand of irrigated land ($irrwd$) and the land area under irrigation (x_7) provides an indication of the maximum sustainable irrigated land area at that time (x_{7max}). When the maximum sustainable irrigated land area is smaller than the area under irrigation, irrigated land is converted into rain-fed agriculture over a certain adjustment time (ad_{73}). The rate at which this conversion occurs is called the irrigation to rain fed rate (x_{73}).

$$\frac{d}{dt}x_7 = x_{71} - x_{72} - x_{73}$$
$$\frac{d}{dt}x_8 = x_{81} - x_{82} + x_{73}$$
$$x_{71} = \big(x_4 - (x_5 + x_6)\big). ad_{71} \text{ if } x_4 > (x_5 + x_6) \text{ and 0 otherwise}$$
$$x_{72} = \big(x_4 - (x_5 + x_6)\big). {}^{x_7}\!/_{(x_7 + x_8)} \text{ if } x_4 < (x_5 + x_6) \text{ and 0 otherwise}$$
$$x_{73} = {}^{(x_7 - x_{7max})}\!\Big/_{ad_{73}} \text{ if } x_{7max} < x_7 \text{ and 0 otherwise}$$

$$x_{7max} = x_7 . irrwd$$
$$x_{81} = \big(x_4 - (x_5 + x_6)\big). ad_{81} \text{ if } x_4 > (x_5 + x_6) \text{ and 0 otherwise}$$
$$x_{82} = \big(x_4 - (x_5 + x_6)\big). {}^{x_8}\!/_{(x_7 + x_8)} \text{ if } x_4 < (x_5 + x_6) \text{ and 0 otherwise}$$

WATER AND FOOD SHORTAGES

The food requirement of the coastal community is simply modeled as the product of the population and an annual food requirement per person (fpp). This requirement is then compared with the total yield from agriculture, which comprises the yield from the irrigated lands and the yield from the non-irrigated lands. The yield of the irrigated lands is detrimentally affected by the chloride content of the groundwater according to the relation given in Saysel & Barlas (2001). This effect is captured in the function $syf(x_3)$.

$$short_{food} = x_1 . fpp - yield_{total} \text{ if } x_1 . fpp > yield_{total} \text{ and 0 otherwise}$$
$$yield_{total} = x_7 . yield_{irr} . syf(x_3) - x_8 . yield_{non-irr}$$

The supply of water to the different demand sectors occurs on the basis of proportional demand. When water is plentiful everyone’s water demands are met, but when water is short the allocation is made depending on the fraction of the total demand required by the different sectors.

$$supply_{domestic} = x_{24}.demand_{domestic}/demand_{total}$$
$$supply_{industrial} = x_{24}.demand_{industrial}/demand_{total}$$
$$supply_{agriculture} = x_{24}.demand_{dagriculture}/demand_{total}$$

where $demand_{total}$is the sum of the domestic, industrial and agricultural water demands.

The domestic water shortage is then given by the difference between the domestic water demand and the domestic water supply.

$short_{water} = demand_{domestic} - supply_{domestic}$ if $demand_{domestic} > supply_{domestic}$ and 0 otherwise

This completes the description of the coastal community aquifer model.

3 A NEW APPROACH TO STUDYING THE RESILIENCE OF AGRICULTURAL COMMUNITIES IN SEMI-ARID COASTAL AREAS: EXPLORATORY MODELING AND ANALYSIS

Most models are intended to be predictive and use consolidative modeling techniques, in which known facts are consolidated into a single ’best estimate’ model. The consolidated model is subsequently used to predict system behavior (Hodges, 1991, Hodges and Dewar, 1992). In such uses, the model is assumed to be an accurate representation of that portion of the real world being analyzed. However, the consolidative approach is valid only when there is sufficient knowledge at the appropriate level and of adequate quality available – that is, only when we are able to validate the model in a strict empirical sense. We can validate models only if the situation is observable and measurable, the underlying structure is constant over time, and the phenomenon permits the collection of sufficient data (Hodges and Dewar, 1992). Unfortunately, for many systems, such as the socio-ecological coastal communities system, these conditions are not med. This may be due to a variety of factors, but is fundamentally a matter of not knowing enough to make predictions (Cambell et al., 1985, Hodges and Dewar, 1992). Many scientists have realized this. Some claim “the forecast is always wrong” (Ascher, 1978); others say such predictive models are “bad” (Hodges, 1991, Hodges and Dewar, 1992), “wrong” (Sterman, 2002), or “useless” (Pilkey and Pilkey-Jarvis, 2007). Decisionmaking about such systems for which our ability to predict is severely limited are is sometimes called decisionmaking under deep uncertainty. Decisionmaking under deep uncertainty is defined as situations in which decisionmakers do not know or cannot agree on a system model, the prior probabilities for the uncertain parameters of the system model, and/or how to value the outcomes (Lempert et al., 2002).

In case of decisionmaking under deep uncertainty, the potential for using a consolidative modeling approach is limited. However, there is still a wealth of information, knowledge, and data available that can be used to inform decisionmaking. Exploratory Modeling and Analysis (EMA) is a research methodology that uses computational experiments to analyze complex and uncertain systems (Bankes, 1993, Agusdinata, 2008). EMA specifies multiple models that are consistent with the available information and the implications of these models are explored. A single model run drawn from this set of models is not a prediction. Rather, it provides a computational experiment that reveals how the world would behave if the assumptions any particular model makes about the various uncertainties were correct. By conducting many such computational experiments, one can explore the implications of the various assumptions. EMA aims at offering support for exploring this set of models across the range of plausible parameter values and drawing valid inferences from this exploration (Bankes, 1993, Agusdinata, 2008). From analyzing the results of this series of experiments, analysts can draw valid inferences that can be used for decisionmaking, without falling into the pitfall of trying to predict that which is unpredictable.

The basic steps in EMA are: (1) conceptualize the policy problem, (2) specify the uncertainties relevant for policy analysis, (3) develop a fast and simple model of the system of interest, (4) design and perform computational experiments, (5) explore and display the outcomes of the computational experiments to reveal useful patterns of system behavior, (6) make policy recommendations (Agusdinata, 2008). EMA is a new, innovative research approach to supporting policymaking under deep uncertainty and has been applied to various climate change related cases (Lempert et al., 2003, Agusdinata, 2008).

4 RESULTS

In section 2, the policy problem (ema step 1) and a model of the system of interest (ema step 3) have already been introduced. In this section, the uncertainties and the experimental setup will shortly be discussed and the results analyzed.

4.1 Uncertainties

Table 1 presents an overview of the uncertainties that are explored in the EMA study of the Coastal Community Aquifer model. In total, 13 uncertainties are explored across the specified range. A number of the uncertainties are represented by multiplier factors that will be used to alter the base value of the corresponding functions. For example, the birth rate is described by a non-linear function representing the time-depended variation of births per 1000 people, by multiplying this with a multiplier factor ranged between 0.8 and 1.2, up to twenty percent more or less births per 1000 people can be simulated.

Table 1: The uncertainties and their ranges

Model variable	**description**	**range**
Births $bf(t)$	Multiplier factor on the non-linear birth function representing the time-dependent variation in the number of births per 1000 people per year	0.8-1.2
Deaths $df(x_3)$	Multiplier factor on the non-linear death function describing the effect of increased salinization of the ground water on the number of deaths per 1000 people per year	0.8-1.2
Migration in response to water shortage $emf_1(short_{water})$	Multiplier factor on the non linear effects of water shortage on the emigration of people from the region	0.5-1.5
Migration in response to food shortage $emf_2(short_{food})$	Multiplier factor on the non linear effects of food shortage on the emigration of people from the region	0.5-1.5
Slope of diffusion lookup function $dif(l(x_2))$	The diffusion of salt from the sea into the aquifer. This is described by a sigmoidal function and varies according to the volume of freshwater in the aquifer. The sigmoid contains a parameter *beta* that affects the slope of the sigmoid	0.5-5
$DELAY(x_{22}, 6\ yr)$	Seepage of salts from irrigated lands into the aquifer. The time factor of 6 years in this third order exponential material delay is adjusted using a multiplier factor.	4-8 years
adj	Multiplier factor alters the adjustment time for land use change from agriculture to urban land. The time it takes for irrigated agricultural land to be converted into non -agricultural land	Change by factor of 0.8 - 1.2
Salt effect on agricultural yield	Multiplier factor on a non-linear relation between salt concentration and the agricultural yield	0.8-1.2
Adaptation time in response to water	Adaptation time of agricultural area in response to water shortage	1-10 years
Adaptation time of non-agricultural land into irrigated land	The time it takes for non - agricultural land to be converted into irrigated agricultural land	0.01-0.5 year
Adaptation time of non-	The time it takes for non - agricultural land to be converted into	0.01-0.5 year

agricultural land into non-irrigated land	non-irrigated agricultural land	
Adaptation times of non-irrigated agricultural area in response to other land usages	The time it takes for non-irrigated agricultural land to be converted into non -agricultural land	0.5-2 year
Technological developments in irrigation	Multiplier factor on the reduction in water usage of irrigated agriculture owing to technological innovation	0.005,0.02

4.2 Experimental setup

The model is implemented in Vensim. Through the Vensim DLL, the model is executed from Python. Python is an open source high level programming language. Extensive open source libraries for scientific computing, jointly known as scipy, are readily available. Using these libraries, a latin hypercube sample across the specified uncertainties is generated consisting of a total of 10.000 cases. Given our stated interest in understanding system behavior, a uniform distribution is assumed for all uncertainties. By assuming a uniform, an effective sampling of the space of possible parameterizations of the model takes place. The assumed uniform distribution should not be interpreted as a laplacian prior. For the population, groundwater volume, amount of salt in the aquifer, the agricultural yield, water shortage, and food balance, the time series data is extracted and stored, together with the values for the uncertainties.

4.3 Analysis of Results

Figure 3 shows the results for a subset of all the runs. In total, 2000 randomly selected runs are visualized here. As can be seen, the model can generate quite a range of different outcomes. Given the specified uncertainties, it is possible that the system collapses, finds a stable level of acceptable functioning, and collapses followed by a gradual restoration. Figure 4 shows a histogram for the end states of the specified indicators. These results show that a wide range of outcomes are possible. With respect to population, in the majority of cases the level of population is about equal to or lower then the initial value, suggesting that the system has limited capability for sustaining a larger population. Looking at the salt concentration, it is clear that in a large majority of cases, a significant contamination of the aquifer takes place. Figure 5 shows the performance envelops for the indicators. That is, the lines show the maximum and minimum values across all the runs for each of the time steps for which data has been saved.

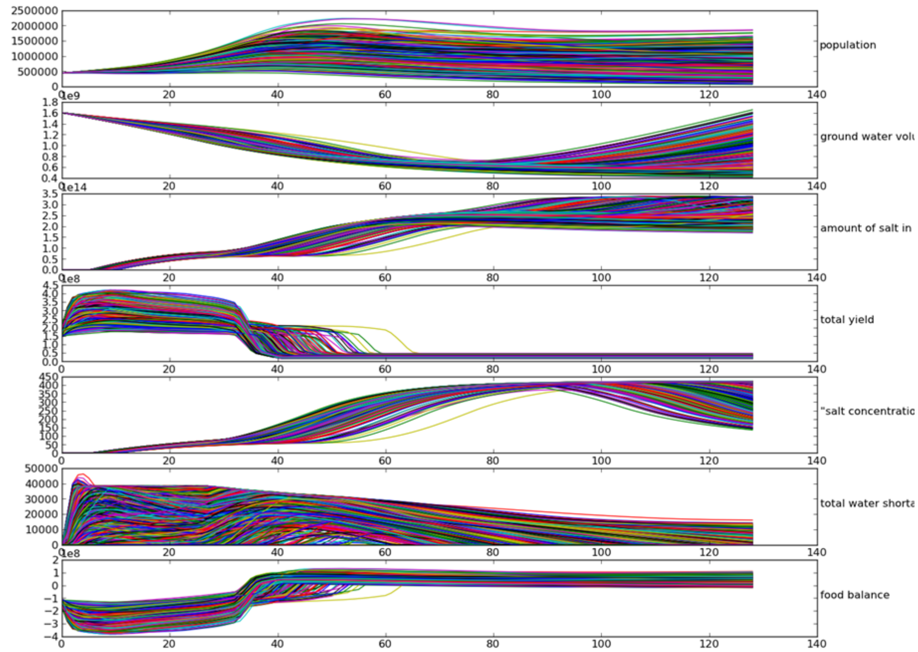

Figure 3: Results for a subset of all the runs

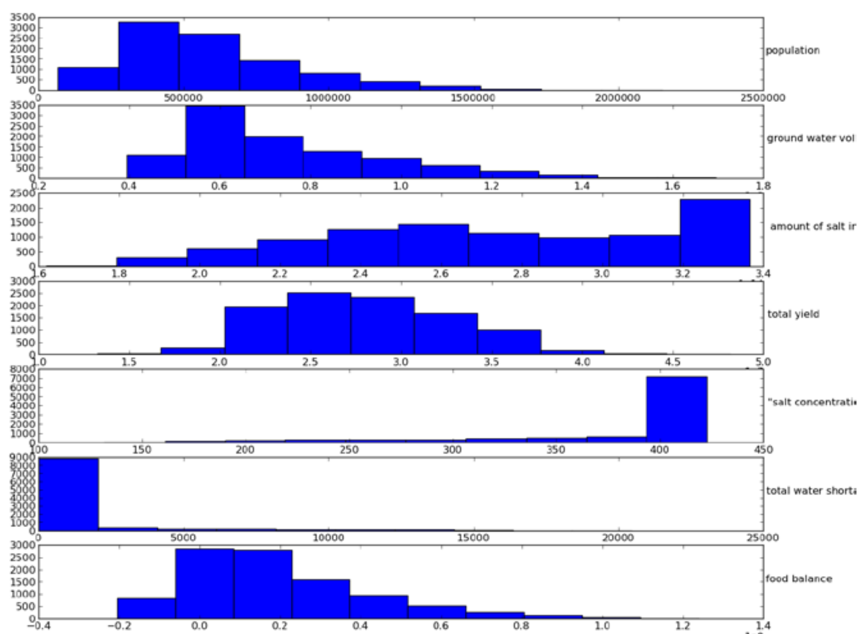

Figure 4: Distribution of outcomes at end of runtime

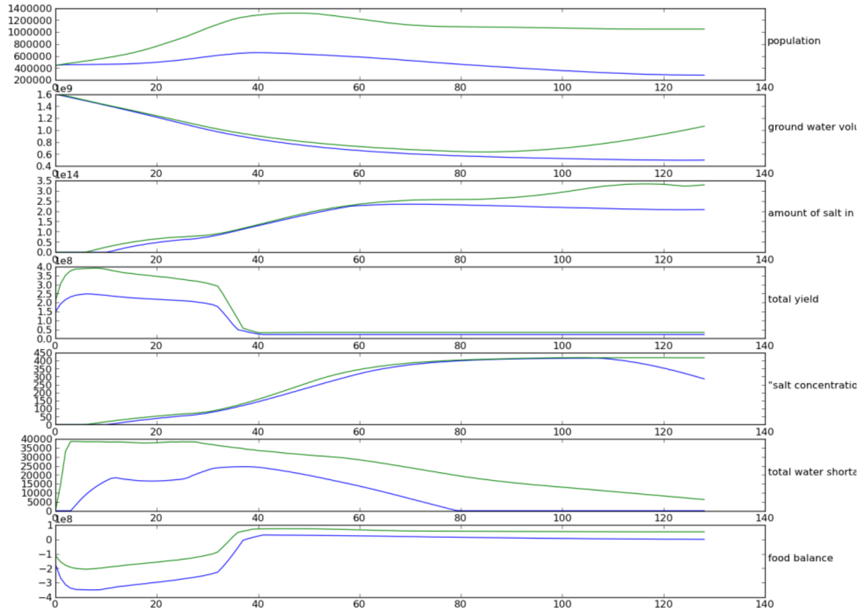

Figure 5: Performance Envelopes for key outcomes

The next step is to create insight into which ranges of values for the various uncertainties result in which outcomes. That is, insight into the mapping from inputs to outputs is needed. One technique that can be employed for this are classification and regression trees. These trees are well established in the data mining and machine learning communities. There are an effective way of displaying which values on specific attributes result in what kind of outcome. Figure 6 in the appendix shows a regression tree for water shortage. By following this tree, one can how the various uncertainties affect the outcomes for water shortage. Similar trees can also be generated for other key outcomes. These trees enable decisionmakers to explore the implications of the various uncertainties. For example, for water shortage, the three most important uncertainties are the birth multiplier, the technological development in irrigation, and the death multiplier. That is, if the population grows quickly, and irrigation does not improve in efficiency, typically, the water shortage will be high. These insights can be used as input to decisionmaking and support the design of effective policies for managing the coastal community.

5 CONCLUDING REMARKS

In this paper, we introduced a simple generic model of the interdependency of a coastal community, its water resource, its water use, and land use practice. The aim of this model was to provide insight into the extent of the vulnerability of coastal communities to climate change. This model has been combined with a scenario generator, exploring the behavior of the model over a wide range. This exploration reveals that in fact these coastal communities are very vulnerable. under almost all the conditions, the system collapses, resulting in a large number of emigrants. Suggesting that the modeled adaptation mechanism of the system are not able to avoid a collapse. Through a classification and regression tree a mapping of inputs to outputs is made. This provides a first step towards designing effective management strategies.

Further research is however needed. First and foremost, in this paper we barely touched upon the main effects of climate change, namely sea level rise and potential long during droughts. Moreover, the current model is a very simplified representation. A slightly more elaborate description of the industry sector is necessary. Moreover, the current model implicitly assumes that all the available land is used. Thus, even if population is very low, a large portion of the land is being used for agriculture. Finally, the current model only takes into account the salinization of the top soil. Another important issue, however, is the salinization of the top soil. Finally, there is a need to explore the behavior across different sizes of the aquifer.

REFERENCES

AGUSDINATA, D. B. 2008. *Exploratory Modeling and Analysis: A promising method to deal with deep uncertainty.* Ph.D. thesis Ph.D. thesis, Delft University of Technology.

ASCHER, W. 1978. *Forecasting: An Appraisal for Policy Makers and Planners,* Baltimore, Johns Hopkins University Press.

BANKES, S. 1993. Exploratory Modeling for Policy Analysis. *Operations Research,* 4**,** 435-449.

BARLOW, P.M. 2003. Ground water in freshwater-saltwater environments of the Atlantic coast. USGS Circular 1262. Reston, Virginia: USGS. (http://pubs.usgs.gov/circ/2003/circ1262/#heading144463296 accessed on 28 January 2011)

CAMBELL, D., CRUTCHFIELD, J., FARMER, D. & JEN, E. 1985. Experimental Mathematics"the role of computation in nonlinear science. *Communications of the ACM,* 28**,** 374-384.

EEA. 1999. Groundwater quality and quantity in Europe. Environmental assessment report No 3. European Environment Agency. Copenhagen. Indicator factsheet (WQ03b) version 01.10.03 http://www.eea.europa.eu/data-and-maps/indicators/saltwater-intrusion/saltwater-intrusion accessed on 28 January 2011).

HODGES, J. S. 1991. Six (or so) Things You Can Do With a Bad Model. *Operations Research,* 39**,** 355-365.

HODGES, J. S. & DEWAR, J. A. 1992. Is it You or Your Model Talking? A Framework for Model Validation. Santa Monica: RAND.

HOEKSTRA, A. Y. 1998. *Perspectives on Water: An Integrated Model-Based Exploration of the Future.* PhD, Delft University of Technology.

IPCC. 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Working Group II Contribution to the Intergovernmental Panel on Climate Change. Fourth Assessment Report. Summary for Policymakers (13 April 2007). (http://www.meteotrentino.it/clima/pdf/rapporti_meteo/IPCC_Impacts_Adaptation_and_Vulnerability.pdf accessed on 28 January 2011).

KIRKWOOD, C. W. 1998. System Dynamic Methods: A Quick Introduction. version 1 { 4/1/98). Ventana Systems Inc. (http://nutritionmodels.tamu.edu/copyrighted_papers/Kirkwood1998.pdf accessed 15 February 2011).

KOOI, H. & Groen, J. 2000. Modes of seawater intrusion during transgressions. *Water Resources Research* 36, no. 12: 3581–3589.

LEMPERT, R. J., POPPER, S. & BANKES, S. 2002. Confronting Surprise. *Social Science Computer Review,* 20**,** 420-439.

LEMPERT, R. J., POPPER, S. & BANKES, S. 2003. Shaping the Next One Hundred Years: New Methods for Quantitative, Long Term Policy Analysis. Santa Monica: RAND.

MEADOWS, D. H. 1985. Mdels of Modeling. In: D.H. Meadows, *The Electronic Oracle.* Chippenham, Wiltshire ISBN 0-471-90558. pp 19-90.

NARAYAN, K.A., C. SCHLEEBERGE, P.B. CHARLESWOOD, & BRISTOW, K. L. 2003. Effects of groundwater pumping on saltwater intrusion in the lower Burdekin Delta, North Queensland. In MODSIM 2003 International Congress on modelling and simulation, ed. A.D.Post, 206–211. Perth, Australia: Modelling and Simulation Society of Australia and New Zealand.

NRC. 2011. Climate Change Impacts and Adaptation: A Canadian Perspective. Coastal Zone. Natural Resources Canada. (http://adaptation.nrcan.gc.ca/perspective/summary_8_e.php accessed on 28 January 2011)

ORREL, D. & MCSHARRY, P. 2009. System Economics: Overcoming the Pitfalls of Forecasting Models via a Multidisciplinary Approach. *International Journal of Forecasting*, 25**,** 734-743.

PILKEY, O. H. & PILKEY-JARVIS, L. 2007. *Useless Arithmetic: Why Environmental Scientists Can't Predict the Future*, New York, USA, Columbia University Press.

STERMAN, J. D. 2002. All models are wrong: reflections on becoming a systems scientist. *System Dynamics Review*, 18**,** 501-531.

SALES, R. F. M. 2008. Mainstreaming community-based adaptation to climate variability and sea-level rise into Integrated Coastal Management: the case of Cavite City, Philippines. *Community and Habitat* 13, (http://www.prrm.org/publications/comhab13/mainstreaming.htm accessed on 28 January 2011).

SAYSEL, A. K., BARLAS, Y. & YENIGUN, O. 2002. Environmental sustainability in an agricultural development project: a system dynamics approach. *Journal of Environmental Management* 64, 1-14.

SAYSEL, A. K. & BARLAS, Y. A dynamic model of salinization on irrigated lands. *Ecological Modelling* 139, 177-199.

SLINGER, J. H. 2010. Too much salt for our taste. Salt intrusion problems in the Omahara aquifer. Case description for the spm2931 continuous modelling project. Delft University of Technology, delft, Netherlands. 16pp.

SLINGER, J.H., YUCEL, G. & PRUYT, E. 2009. Communicating model insights using interactive learning environments. In: Proceedings of the 27th International Conference of the System Dynamics Society (pp 1-8). July 2009. Albuquerque, USA.

APPENDIX

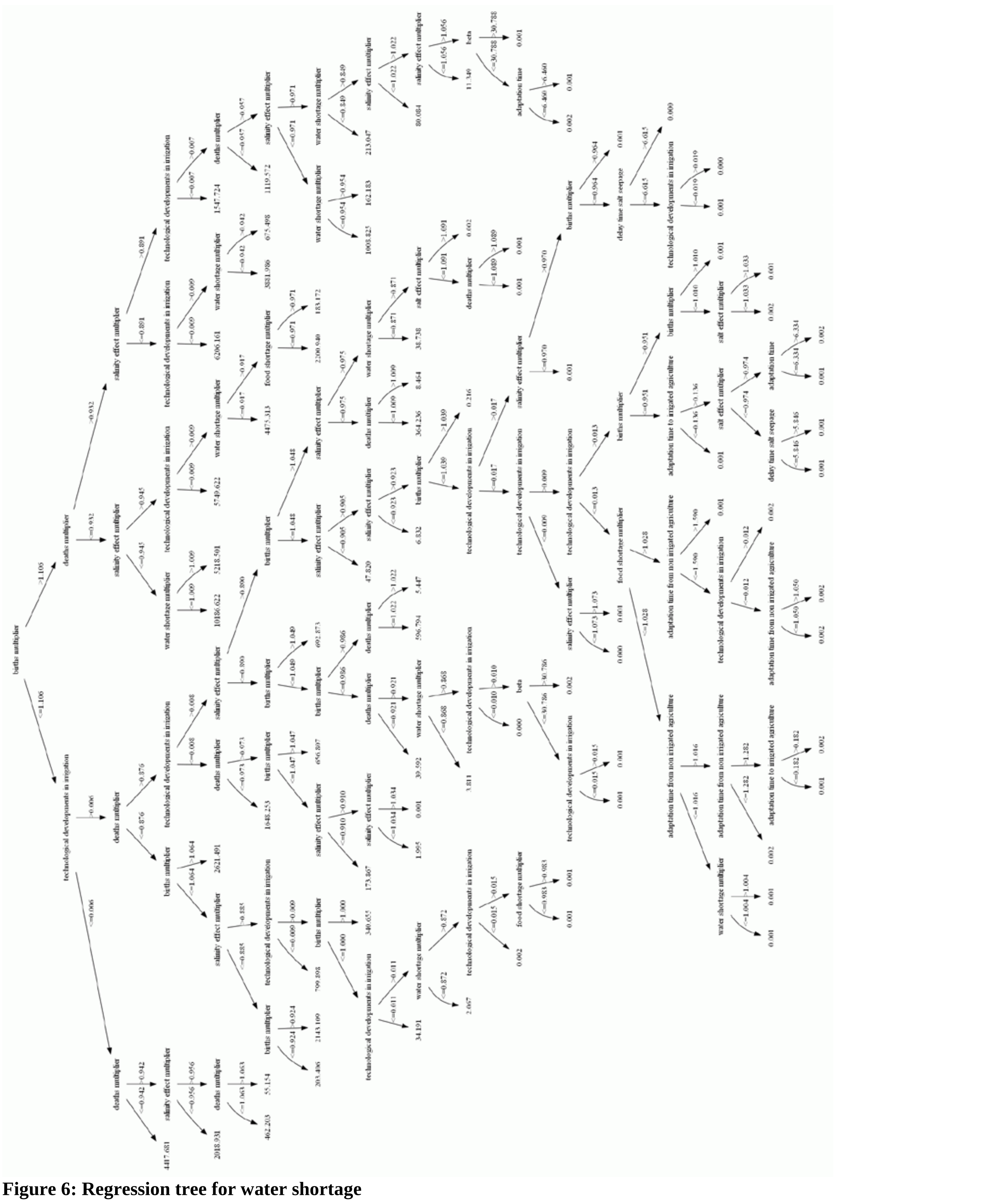

Figure 6: Regression tree for water shortage