A System Dynamics Model-Based Exploratory Analysis of Salt Water Intrusion in Coastal Aquifers

Jan .H. Kwakkel and Jill .S. Slinger
Delft University of Technology
Faculty of Technology, Policy and Management
Jaffalaan 5
2628 BX Delft, The Netherlands
+31(0)15 27 88487
J.H.Kwakkel@tudelft.nl
J.S.Slinger@tudelft.nl

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 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 system dynamics 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 system model in turn is coupled to a powerful scenario generator, which is capable of producing a comprehensive range of plausible future scenarios. 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 a 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.

Key words: salt intrusion, coastal aquifer, salinization, freshwater management, system dynamics, exploratory modeling and analysis, deep uncertainty, policy analysis

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. The analysis of such socio-ecological systems is further complicated by the omnipresence of a wide variety of uncertainties, related to future climate change, other external forces such as technological developments, and uncertainty about the internal functioning of the system

In this paper, we seek to address this gap first by developing a simple yet generic system dynamics model of a coastal community dependent upon its groundwater resources. This model covers population, land use including agriculture, and the groundwater reserve. The Coastal Community Aquifer 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, Popper, and Bankes 2003), thus allowing to explore the behavior of the model across a wide range of plausible future developments.

We explore the behavior of the systems model across the wide range of scenarios and analyze the implications of the scenarios for 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.

After first addressing the need for an exploratory modeling approach to studying the vulnerability of coastal communities who are dependent on groundwater resources, and describing the fit between system dynamics and exploratory modeling techniques (section 2), we move on to describing the Coastal Community Aquifer model (section 3). The results of applying exploratory modeling techniques to the analysis of the potential range of system dynamics model outcomes are described in section 4. First the base case results are described, next the range of uncertainties that are tested are detailed and the manner in which this is undertaken is described in the experimental set-up. Finally the results are depicted and further research is delineated.

2 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 – 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 met. 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). Decision making about systems for which our ability to predict is severely limited is sometimes termed decision making under deep uncertainty. Decision making under deep uncertainty is typically encountered in situation 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 Deep uncertainty bears a strong family resemblance to the wider literatures on wicked problems (Churchman 1967) and messy problems (Ackoff 1974). It can be argued that decision making under deep uncertainty is a subclass of wicked problems or messy problems. Analytically, deep uncertainty can be defined as being able to enumerate multiple alternatives for how something is or will be without being able or willing to rank order the alternatives in terms of how likely or plausible they are judged to be (Kwakkel, Walker, and Marchau 2010).

The potential for using a consolidative modeling approach is limited for decisionmaking under deep uncertainty. 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 represents 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, Popper, and Bankes 2003; Agusdinata 2008).

EMA takes a particular stance on how models can be usefully applied to inform decisionmaking despite their limited predictive power. This stance is independent of the type of modeling paradigm that is being used. EMA researchers have utilized agent based models, spreadsheet models, operation research models, and domain specific modeling approaches. Recently, there has been an upsurge in combining EMA with exploratory System Dynamics models. EMA and System Dynamics are perfect partners (Pruyt 2010, 2010; Pruyt and Hamarat 2010). System dynamics is traditionally used for modeling and simulating dynamically complex issues, analyzing the resulting non-linear behaviors over time, and developing and testing structural policies. Many dynamically complex problems are characterized by deep uncertainty, since in case of dynamic complex issues the cause effect relations are subtle (Senge 1990). The omnipresence of uncertainty has been recognized by many system dynamicists and is the underlying motivation for interpreting the quantitative results of system dynamics models qualitatively (e.g. in term of modes of behaviors or behavioral trajectories)(Meadows and Robinson 1985; Pruyt 2007). This qualitative interpretation of model results is compatible with the interpretation of model results in EMA.

3 A Model of Salinization in a Semi-Arid Coastal Agricultural Community

3.1 Conceptual description of the model

At present, various integrated System Dynamic water cycle models exist at both global and regional scales. These models have been used to define global or regional limits to the use of blue water. On a global scale, AQUA (Hoekstra 1998), WorldWater (Simonovic 2002) and ANEMI (Davies 2007; Davies and Simonovic 2011) are prime examples. On a regional scale, a several System Dynamic models are available. Most of these are prepared to analyze socio-economic development in relation to water resources at a basin level. Aqua (Hoekstra 1998) can be used for the regional level, but case specific models exist as well. Saysel and Barlas (2001; 2000) present a model for the South-eastern Anatolian Project in semiarid South-eastern Turkey. Simonovic and Rajasekaram (2004) present a System Dynamics model of water resources and water use for Canada, which borrows various constructions from the WorldWater model.

The coastal aquifer is conceptualized as a single hydro stratigraphic unit of sand/gravel, 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 (adapted 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 10^9 m^3.

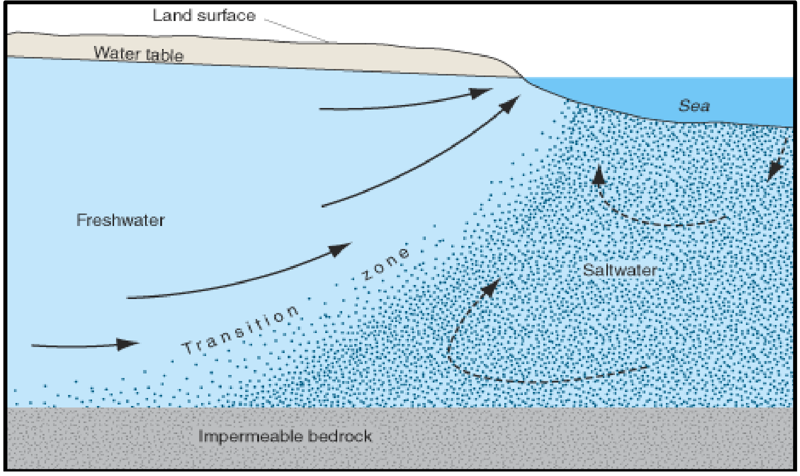

Figure 1: Cross-section through a uniform sand aquifer indicating the fresh groundwater resource on the left, the sea water on the right and the halocline forming the interface or transition zone between the two water bodies (from Barlow 2003).

In contrast to many groundwater models (Barlow 2003; Kooi and Groen 2000; Narayan et al. 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.

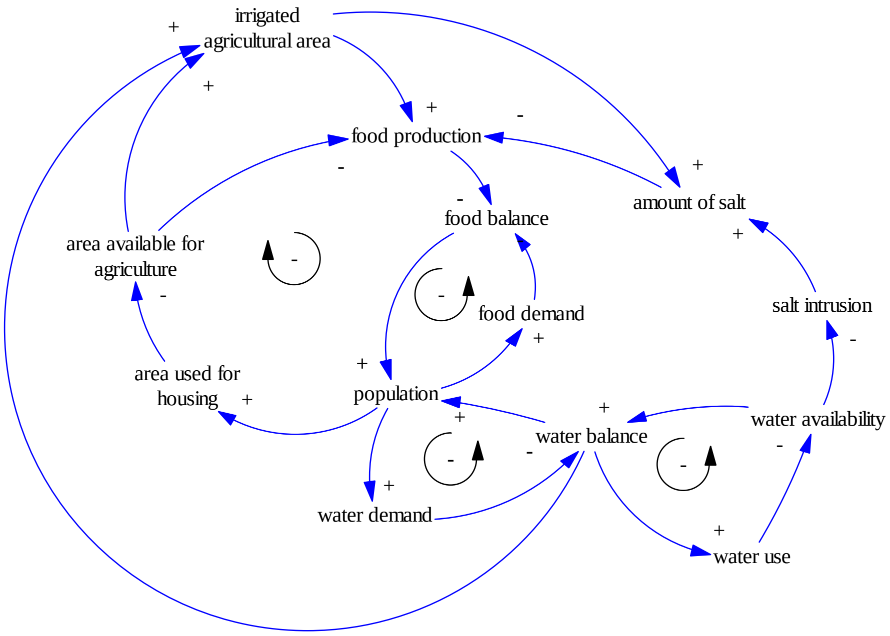

Figure 2: High level conceptual diagram of the main feedbacks

Figure 2 shows the main feedbacks in the model. The population in the area is constrained by both the availability of land and the availability of water. If the population grows, the land area available for agriculture declines, in turn resulting in a decline of food production. The decline of food production results in a negative food balance, resulting in a decline in population. If the population grows, the water demand will increase. The increasing water demand lead via water balance to an increase in use. The increasing use negatively affects the available water, which, via the water balance leads to a decline in the population. Water availability and land availability both affect the amount of land that is being irrigated. The more land is irrigated, the higher the food production. Irrigation of land leads to an increase of salt in the aquifer. Salt is also increased due to salt intrusion. Salt intrusion increases if water availability decreases. The buildup of salt in the aquifer in turn negatively affects food production. The current version of the model does not the buildup of salt in the top soil, but does not yet translate it to desertification and the resulting loss of land for agriculture.

The model as presented is a generic model. Parameter values related to water demand from agriculture and population are in line with values used in World Water and Anemi (Davies and Simonovic 2011; Simonovic 2002). The buildup of salt in the top soil is inspired by Saysel and Barlas (2001; 2000).

3.2 Detailed model specification

The coastal community aquifer model (CCA) comprises four 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 (Barlow 2003; Narayan et al. 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 and 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.

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

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, Barlas, and Yenigun 2000). 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 and Barlas 2001; Saysel, Barlas, and Yenigun 2000). 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}).

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

$x_{73} = {(x_7 - x_{7max})}\big/{ad_{73}}$ if $x_{7max} < x_7$ and 0 otherwise

$x_{7max} = x_7.irrwd$
$x_{81} = \big(x_4 - (x_5 + x_6)\big).ad_{81}$ if $x_4 > (x_5 + x_6)$ and 0 otherwise
$x_{82} = \big(x_4 - (x_5 + x_6)\big).{x_8}\big/{(x_7 + x_8)}$ if $x_4 < (x_5 + x_6)$ 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 $syf(x_3)$.
$short_{food} = x_1.fpp - yield_{total}$ if $x_1.fpp > yield_{total}$ 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. The model is implemented in the Vensim software. The stock and flow diagrams are presented in the appendix.

4 Results

In section 3, 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 be discussed shortly 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 as 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-dependent 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 nonlinear 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 nonlinear 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
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-agricultural land into non-irrigated land	The time it takes for non - agricultural land to be converted into non-irrigated agricultural land	0.01-0.5 year
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
Evaporation constant	The fraction of rainfall that evaporates	0.4-0.8
Water usage by crops	The amount of water crops extract from the top soil.	0.95 – 1.25 m/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 using the ‘EMA workbench’. Python is an open source high level programming language. Extensive open source libraries for scientific computing, jointly known as Scipy (http://www.scipy.org/), are readily available. The EMA workbench offers functionality similar to that available in most System Dynamics software packages. We use it, because of its convenience in easily specifying the parameters and their ranges, its ease of storing results and the support it offers for subsequent analysis of the results using various machine learning algorithms. Using the EMA workbench, a Latin Hypercube sample (Iman, Helton, and Cambell 1981) 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 distribution, an effective sampling of the space of possible parameterizations of the model takes place. The assumed uniform distribution should not be interpreted as a statement about prior beliefs. For the population, groundwater volume, amount of salt in the aquifer, the agricultural yield, water shortage, and food balance, the time series data are 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, 100 randomly selected runs are visualized here, combined with a Gaussian kernel density estimate of the terminal values. As can be seen, the model typically shows an overshoot and decline dynamic. The population grows up to the point that the salt concentrations in the aquifer becomes passes a threshold after which the agricultural yield declines sharply. This declining yield results in food shortages and the associated exodus of people from the region because of this. It appears that only a few runs deviate from this dynamic, namely those runs that have a slower increase of the population. This is also suggested by the Gaussian kernel density estimate of the end state, which show a clear double hump.

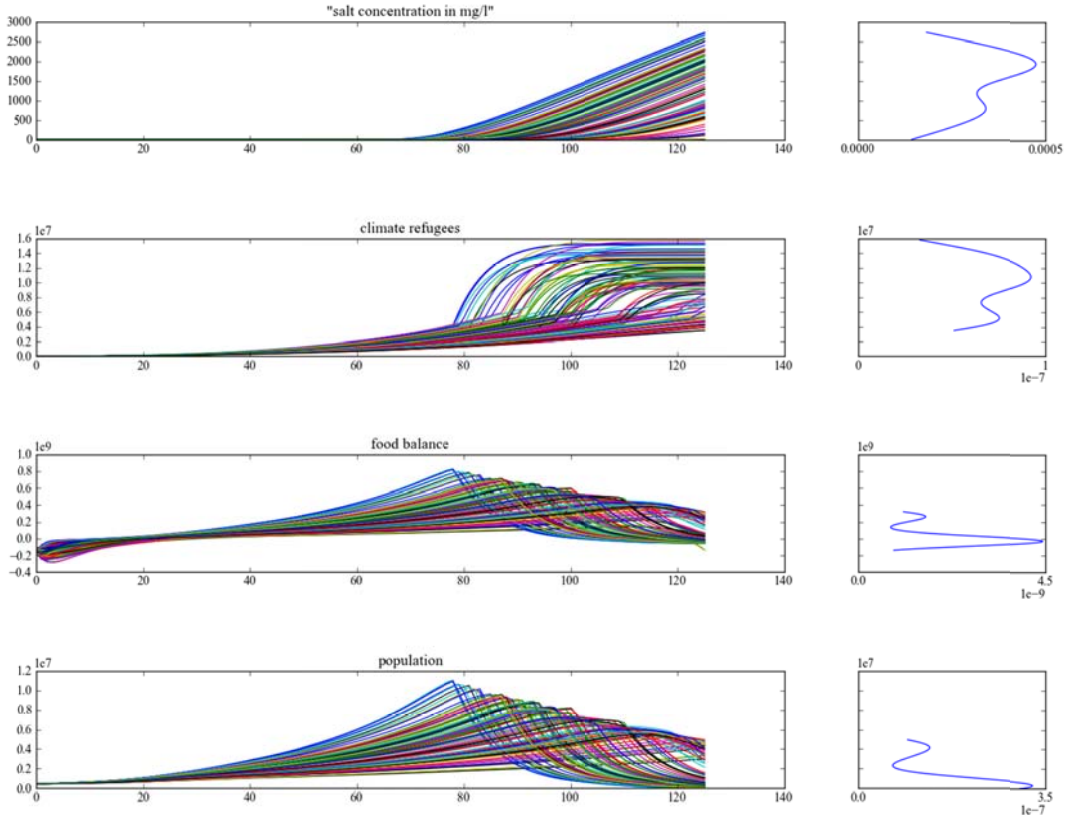

Figure 3: Results for a subset of all the runs

The next step is to develop insight into which ranges of values for the various uncertainties result in which outcomes. That is, insight into the mapping of inputs to outputs is needed. One technique that can be employed for this is the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999; Chong and Jun 2008). PRIM can be used for data analytic questions where the analyst tries to find combinations of values for input variables that result in similar characteristic values for the outcome variables. Specifically, one seeks a set of subspaces of the input variable space within which the values of output variables are considerably different from the average value over the entire domain. PRIM describes these subspaces in the form of ‘boxes’ of the input variable space. PRIM induces boxes by iteratively peeling of small parts of an initial box that covers all the data. For each iteration, all possible new boxes are generated and the one that has the highest increase on the objective function is selected. The iteration stops when the amount of data inside the box falls below a particular user specified threshold. Next, PRIM iteratively adds a small amount of data back to the box by extending it again. This pasting continuous as long as the objective function keeps increasing. This results in a very concise representation, for typically only a limited set of dimensions of the input variable space is restricted. That is, a subspace is characterized by upper and/or lower limits on only a few of the input dimensions.

We used PRIM to identify the subspace of the full uncertainty space that produces a terminal value for the population higher than 2.2 million (an estimate of where the split between the two humps in the kernel density is located). In total 3264 cases meet this criterion. PRIM finds 4, partially overlapping subspaces that have a concentration of cases higher then 0.8. These subspaces are spanned by a relatively low value for the births multiplier, coupled to a high value for the water shortage multiplier and food shortage multiplier. This implies that high values for the end state of the population occur if the net growth of the population is relatively low.

5 Concluding Remarks

In this paper, we introduce 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 in 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 conditions, the system collapses, resulting in a large number of emigrants. This suggests that the modeled adaptation mechanisms of the system are not able to avoid a collapse. Using PRIM, a mapping of inputs to outputs is made. This provides a first step towards designing effective management strategies.

Research into effective management strategies for prolonging the life time of the aquifer is currently underway. In addition, research on further development of the Coastal Community Aquifer model is ongoing. For instance, the inclusion of a salt dispersion mechanism in the model is under study. Moreover, in the current implementation, the population has no impact on how much land is actually producing food, thus, if the population is near zero, there is still a huge production in agriculture. Making the arable land dependent on the population will address this. Related, the model does contain a buildup of salt in the top soil, but this in turn can be translated into a loss of agricultural land due to desertification. This mechanism is currently not present in the model. Another line of research is to complement the existing scenario generators with various climate change scenarios. For example, how will the system evolve if there is an extensive wet period followed by an extensive drought? Finally, so far we have only explored the ranges of behaviors that are possible using a Latin Hypercube sampling approach. A more directed search, utilizing Active Non-linear testing (Miller 1998) can be utilized to find worst case scenarios under the specified ranges of the various uncertain parameters.

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APPENDIX 1

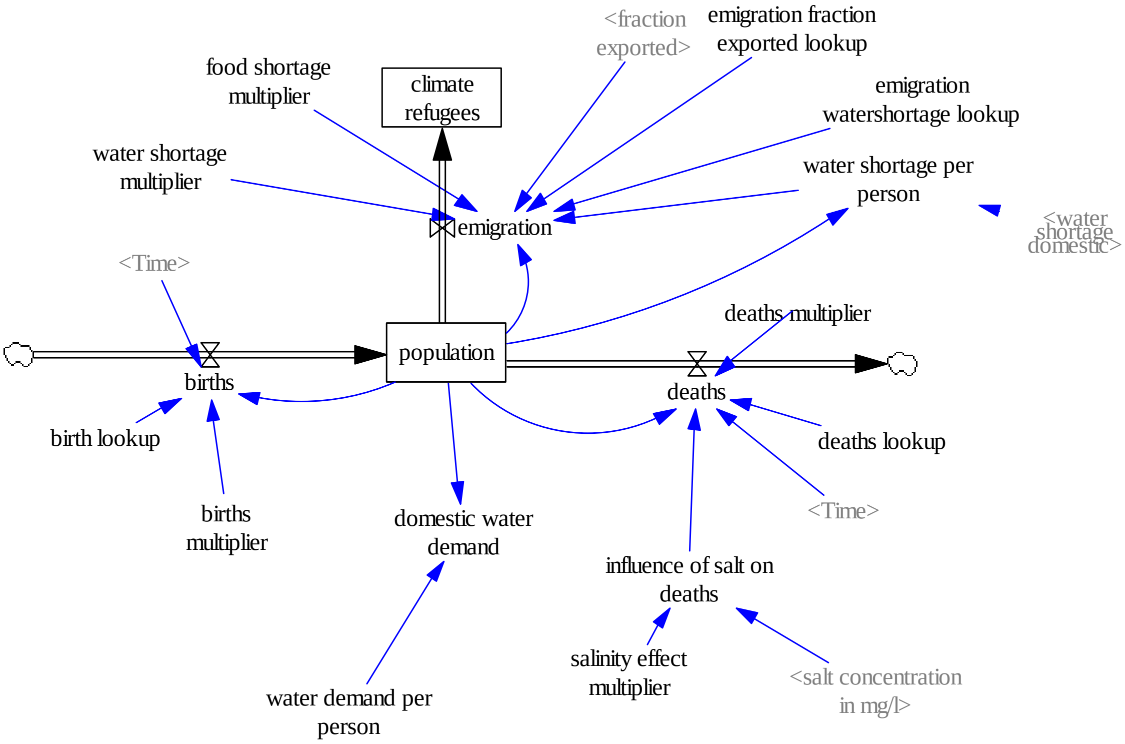

Figure 4: Population

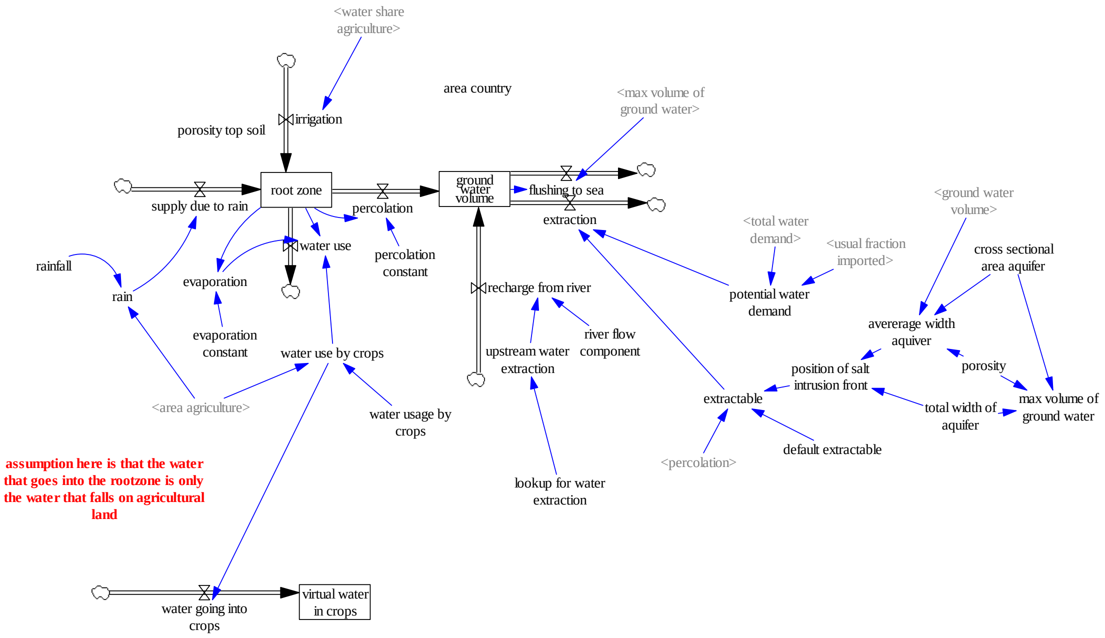

Figure 5: Groundwater reserve

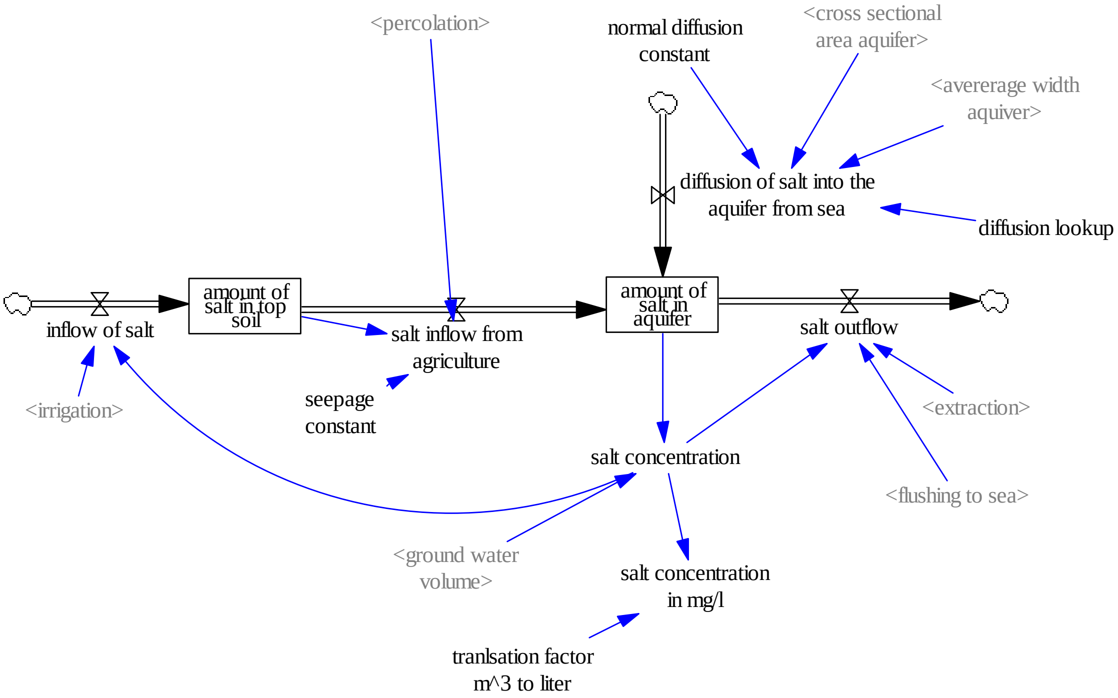

Figure 6: Salt

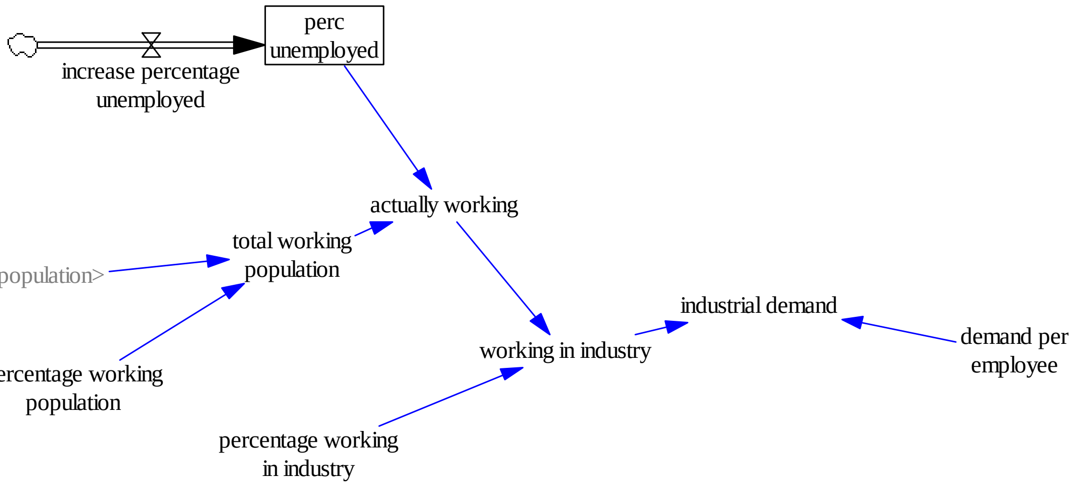

Figure 7: Labor

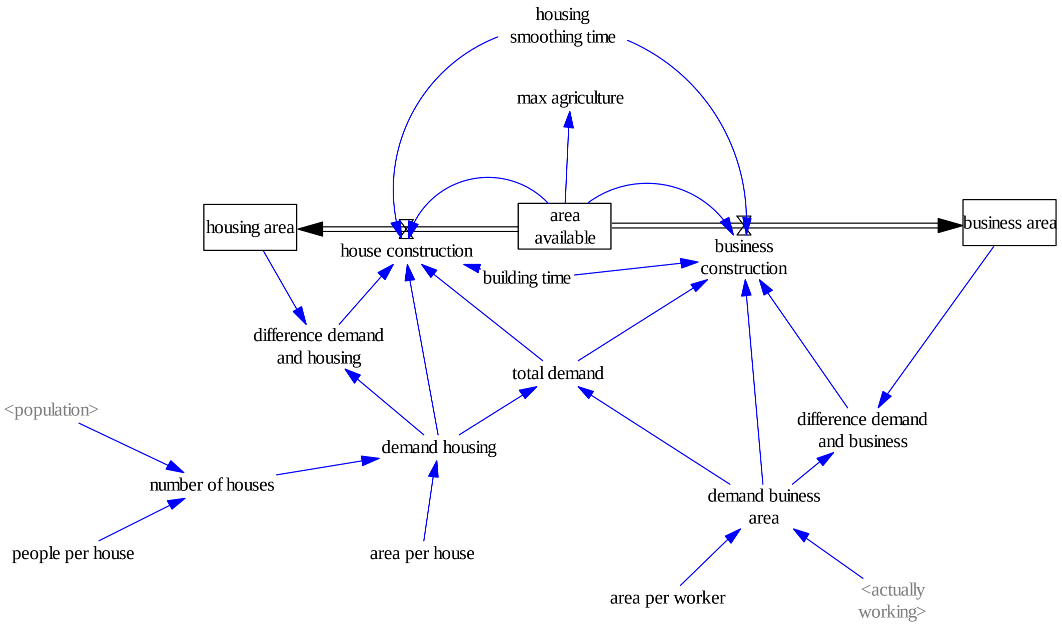

Figure 8: Land use for population and businesses

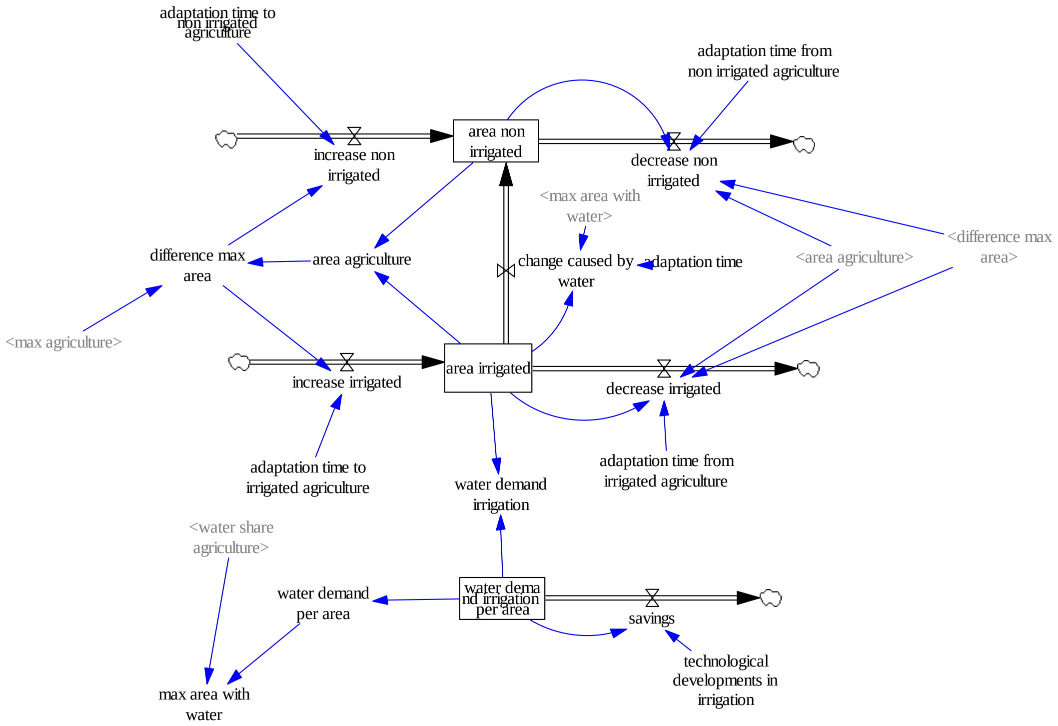

Figure 9: Land use agriculture