STUDYING COUPLED HUMAN AND NATURAL SYSTEMS FROM A DECENTRALIZED PERSPECTIVE: THE CASE OF AGENT-BASED AND DECENTRALIZED MODELING

BY

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THESIS

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Abstract

The science of coupled human and natural systems deals with the interactions between humans and their environment. This science focuses on the complex dynamics and patterns that emerge through these interactions. One of the most insightful ways to study coupled human and natural systems consists in developing models to reproduce the patterns seen in these systems. Models of coupled human and natural systems are particular in the sense that they require the integration of knowledge from various and differing fields such as economics, social sciences, ecology, hydrology, biology, climate sciences and many others. In this thesis, we claim that most coupled human and natural systems are decentralized and would better be modeled from a decentralized perspective. Agent-based models, especially can be very useful to model human systems. A review of the literature shows that agent-based modeling is a commonly used tool in all the fields related to coupled human and natural systems such as socio-ecology – or social and ecological systems, hydro-economic systems, socio-hydrology or integrated environmental modeling. While agent-based models present a lot of challenges, they appear as promising tools for the representation of humans in models of coupled human and natural systems.

Using an agent-based model of farmers' decision-making on irrigation, coupled with a model of groundwater flow and aquifer/stream interactions, we studied the role of individuals in a coupled agricultural and hydrologic system. The model was designed to simulate the interactions between farmers pumping groundwater to irrigate their corn fields and the water levels within a portion of the aquifer below the Republican River Basin in the High Plains region in Nebraska. A set of simulations show that incorporating behavioral heterogeneity of individuals in the model leads to the formation of spatial and temporal patterns. In other words, some of the patterns found in the real system could be partially explained by behavioral heterogeneity of farmers. Additionally, we find that model results are more accurate when accounting for individual heterogeneity. Including individuals in the model also helps understand how these individuals are impacted by system dynamics such as new policies or

environmental change. This can prove useful for policy making when knowing the differences between individuals can help devise better policies. The challenge in modeling individuals and their behavior is to decide how complex these models should be. We suggest that individual behavior should be considered as another source of uncertainty rather than a source of unnecessary complexity.

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CHAPTER 1

INTRODUCTION

The science of Coupled Human and Natural Systems (CHANS) emerged as a field in the late 2000s with the publishing of the seminal paper "Complexity of Coupled Human and Natural Systems" in 2007 by Liu et al. (2007b). However, the concept of a human system and a natural system interacting can be traced back to the early 2000s or late 1990s in books such as "Panarchy: understanding transformations in human and natural systems" by Gunderson and Holling (2001) or "Reshaping the built environment: Ecology, ethics, and economics" by Kibert (1999). According to Liu et al. (2007b), the science of CHANS aims at understanding how a human system and a natural system interact to form a whole, a unique complex system. Studying each part of this system separately, as was done before, is not sufficient. CHANS is a branch of complexity science recognizing that dynamic interactions between humans and the environment shape both systems. In this new framework, measuring and modeling the interactions between human and natural systems over days, years, decades and centuries and over a continuum of spatial scales reveals the co-evolution of these systems. Liu et al. (2007b) describe six very different case studies to illustrate how complex patterns emerge from the interactions between the human and the natural systems. These examples are characterized by non-linear dynamics, feedback loops, time lags, heterogeneity and unexpected behaviors. They are also characterized by different spatial and temporal scales.

There are many examples of well-defined CHANS around the world. One of the most obvious interdependencies between humans and their environment is the relationship between humans and climate. It is a complex relationship occurring over very long periods of time. Many societies depend on climate for their survival. But with the advent of climate change, humans realized that it is not a one-sided relationship as human activities have had such a drastic impact on climate. While CHANS usually assume a more tightly coupled relationship between the human and the natural systems, there are still a few interesting examples of humans' dependency on climate. Bucklet et al. (2010) for example explain that the demise of Angkor, the ancient capital of the Khmer Empire in Cambodia, was due to a series of severe droughts and intense monsoons over several decades. While the droughts impacted agriculture and water supply, the monsoons damaged the famous hydraulic infrastructures of the city. Similarly, Haug et al. (2003) suggest that the Maya civilization collapsed because of the decline of rainfall (a critical resource for these societies) over an entire century, leading to more severe and more frequent droughts. Climate can destroy societies but it can also make them prosperous. A recent study by Pederson et al. (2014) shows how Genghis Khan built the largest contiguous land empire in world history with the help of 15 consecutive years of above-average moisture in central Mongolia.

Another example is the feedbacks between humans and ecosystems, the focus of a field called socio-ecology or social and ecological systems. Brashares et al. (2004) shed light on surprising interactions between bushmeat hunting, wildlife decline and fish supply in West Africa. Their study shows that declining fish supplies led to increased hunting in nature reserves, eventually causing sharp drops in biomass of 41 wildlife species. This work highlights the multiple interconnections between humans and their environment. These interconnections are also investigated by Pollnac et al. (2010) in a paper studying "marine reserves as linked social-ecological systems". They study 56 marine reserves in the Philippines, Caribbean and Western Indian Ocean and find that human population density and compliance with reserve rules have the strongest effect on fish biomass. These relationships, however, are different from region to region. These findings show how human populations and fish populations interact with each other and how these interactions are system specific.

What this thesis will focus on is the subset of CHANS in which the natural system is a water system, and more specifically a watershed. There are many examples of societies living within river basins and interacting with the water system, affecting and being affected by the quantity and the quality of the water. The human system generally consists of an agricultural system. A good example of such CHANS within a river basin is provided by Kandasamy et al. (2014) in their study of the Murrumbidgee

River Basin in Australia. In this paper the authors analyze the feedbacks between the human and the water systems over a period of 100 years. They find that these 100 years can be divided into 4 eras with different dynamics characterizing each era. More directly related to this thesis is the CHANS formed by irrigated agriculture in the High Plains Aquifer in the US. This region is dominated by strong interactions between farmers using groundwater and surface water for irrigation, and the underlying aquifer and surrounding river basin. These interactions are bi-directional because of the groundwater and streamflow depletion which leads to higher pumping cost, institutional changes etc. (Scanlon et al., 2012). This specific issue will be described in more detail in Chapter 3.

One key characteristic of CHANS is that they are decentralized and have specific spatial, hierarchal and organizational distributions. This is due to the facts that natural systems are usually spread over wide areas and human systems are by definition decentralized, consisting of networks of individuals, groups, institutions and other entities. Recognizing the inherent decentralized structure of CHANS has significant implications on the way they are studied. From a modeling perspective especially, it is important to decide early-on which framework is more appropriate. It can be expected for example that lumping together water users into one human entity with one homogeneous behavior in a model would lead to very different results than if these water users were all modeled as independent individuals with heterogeneous behaviors.

The purpose of this thesis is to develop knowledge on decentralized modeling of CHANS with an emphasis on Agent-Based Modeling (ABM), a tool widely used to model decentralized entities interacting with each other and with their environment. The emphasis is also on water, a specific case of natural systems which is also critical to both human development and the well-being of all other natural systems – ecosystems, wildlife, forests, climate etc. This work is divided into three main chapters. In Chapter 2, a review of agent-based and decentralized modeling of CHANS is provided. The goal is to give an overview of the current available models and how they have been used. This review includes other reviews, case studies and model development papers. It also includes a presentation of the challenges and opportunities of modeling CHANS with agent-based and decentralized models. Chapter 3 goes one step further by evaluating the role of individuals in modeling CHANS. Here the question is whether it is important or not to use agent-based and decentralized models to account for individuals in such systems as opposed to more simple models. To answer this question, an ABM was developed and coupled to a groundwater model and the integrated model was used to assess the importance of modeling individuals in an agricultural watershed dominated by irrigated agriculture and facing serious environmental problems due to over-pumping of the water resources. The model is used to determine the role of individuals in CHANS.

CHAPTER 2

AGENT-BASED AND DECENTRALIZED MODELING APPLIED TO COUPLED HUMAN AND NATURAL SYSTEMS: A REVIEW

2.1. Modeling Coupled Human and Natural Systems

CHANS are usually modeled with integrated or coupled models to account for both the human and the natural systems. There are many categories of models that belong to the more general category of CHANS models: social-ecological models, hydro-economic models, socio-hydrologic models, integrated environmental models and others. Schlüter et al. (2012) provide an overview of social-ecological systems models. Social-ecological systems are equivalent to CHANS and have been used mainly in social sciences and ecology. They are characterized by strong interactions between an ecological system and a social system including feedbacks, nonlinear dynamics, self-organization and cross-scale interactions. Hydro-economic models are more specific applications of CHANS that are mainly used to study water resources systems. Harou et al. (2009) give an in-depth review of hydro-economic models. These models offer a framework to model water resources systems by integrating hydrologic and environmental aspects as well as engineering and economic aspects, and are ideal tools for conducting integrated water resources management (IWRM). Sivapalan et al. (2012) present a definition of the nascent field of socio-hydrology. Socio-hydrology is the study of the self-organization of people and their co-evolution in the landscape with respect to water availability. It is the science of the long-term feedbacks between people and water. A prototype framework for socio-hydrologic models is introduced by Elshafei et al. (2014) and includes six components: catchment hydrology, population, economics, environment, socioeconomic sensitivity and collective response. Integrated environmental modeling is described in details by Laniak et al. (2013). It is described as "*a discipline inspired by the need to solve increasingly complex real-world problems involving the environment and its relationship to human systems and activities (social and economic)*".

This profusion of fields shows the width and diversity of the science of CHANS. While the models used for natural systems in these fields are already close to reaching their maturity, there is no consensus on how to model human systems yet. Decentralized modeling emerged as a logical tool to study CHANS due to the inherently distributed and decentralized nature of these systems. Agent-based modeling in particular has been widely adopted to model human systems. This chapter provides a literature review of decentralized and agent-based models applied to CHANS, as well as an overview of the main challenges and opportunities for using such models.

2.2. Agent-based and Decentralized Modeling applied to Coupled Human and Natural Systems

As was mentioned in the previous section, ABM has become a common way of modeling the human component in CHANS. There are a number of reviews that cite ABM as one of the tools useful to study CHANS, or even focus specifically on ABM applied to CHANS. An (2012) gives a thorough review of ABMs used to analyze CHANS in her paper “Modeling human decisions in coupled human and natural systems: Review of agent-based models”. She finds that 121 articles describing ABMs developed to study a CHANS were published between 1994 and 2010. According to her review, geographers and ecologists are the main ABM users for CHANS. It is also interesting to note that the top six journals in this field are Ecological Modeling, Environmental Modeling & Software, Environment and Planning B, Geoforum, Journal of Environmental Management, and Agriculture, Ecosystems & Environment. Five out of these six journals focus on ecology or the environment and one focuses on geography. She identifies nine types of decision models used to represent humans in CHANS: microeconomic models, space theory based models, psychosocial and cognitive models, institution-based models, experience- or preference-based decision models (rules of thumb), participatory agent-based modeling, empirical or heuristic rules, evolutionary programming, and assumption and/or calibration-based rules. Filatova et al. (2013) present the challenges and prospects of spatial agent-based models for socio-ecological systems. They identify four main challenges: design and parameterizing of agent decision models; verification, validation and sensitivity analysis; integration of socio-demographic, ecological, and biophysical models; and spatial representation. These challenges will be discussed again in section 2.3. Their paper is a preface to a special issue of Environmental Modelling & Software (one of the journals with the highest accounts of papers describing ABMs as mentioned by An (2012)) on spatial agent-based models for socio-ecological systems, a sign of the interest of this community on the issue. Finally, Kelly et al. (2013)

assess ABM as one of five common tools for integrated environmental modelling and management. They describe three main applications for ABMs based on their review: "*as part of an exploratory participatory modelling process with relatively smaller numbers of stakeholders considering resource competition problems at local scales; as a group decision or management support tool and, as part of a more theoretical or academic study aimed at developing understanding of social and biophysical systems*".

The three general reviews by An (2012), Filatova et al. (2013) and Kelly et al. (2013) presented above illustrate the profusion of articles on ABMs applied to CHANS. Two particularly interesting articles describing specific models were selected and are presented here. The first article by Mialhe et al. (2012) describes an ABM designed to analyze land use dynamics in response to farmer behavior and environmental change. The model specifically focuses on the Pampanga delta in the Philippines, a region subject to a tropical climate with a monsoon season when typhoons are commonplace. Land use in the region was predominantly rice, aquaculture and natural habitat until the 1970s and transitioned to perennial aquaculture in the 2000s. The two types of agents in the model are farmers and investors. Investors buy land when the circumstances are favorable and can later become farmers. Farmers are characterized by different behavioral models and decide on cropping systems adoption. Farmers can be rational, collective-minded or have a bounded rationality. Each type of farmer has different objectives, such as making profits, adopting the same cropping system as their neighbors, following government guidelines or securing a stable income. External variables include typhoons, markets and government recommendations. A set of 12 scenarios was created combining the three behavior types for farmers and four environmental dynamics: no deltaic subsidence, constant subsidence rate, higher subsidence rate after 1990, and higher subsidence rate punctuated by external variables. The 12 scenarios reveal different land use dynamics over the simulation period including an expansion of paddy crops replacing natural habitats, the spread of aquaculture on areas previously unfarmed or devoted to paddy crops, and alternative domination of paddy crops and aquaculture. The model also shows how deltaic subsidence negatively impacts farmers. Farmers' satisfaction slowly changes with the environmental modifications caused by subsidence. This implies that subsidence does not cause radical shifts that would favor one particular cropping system. As can be expected, the model finds that typhoons decrease farmers' profits but their impacts are gradual because of the high profitability of aquaculture. The authors also used the model to assess farmers' behavior adaptation and change with time. In short, Mialhe et al. (2012) provide fascinating insights on the complex dynamics of human and natural systems driven by the interactions between individual behavior, institutions, external economic drivers and environmental changes.

Another example is the model developed by Iwamura et al. (2014) to study how indigenous people of the Rupununi region of Amazonian Guyana interact with their environment through hunting and subsistence agriculture. The model was specifically designed to understand the interactions between demographic growth, hunting, subsistence agriculture, land cover change and animal population. There are four types of agents: land patches, villages, households and animal species. Household agents are driven by an energy requirement satisfaction behavior through hunting and cultivation. They try to achieve a target energy requirement, and if they fail to meet a minimum energy requirement they leave the study area. Land patches represent landscapes and their land cover varies from forest and grassland to water body and cultivated area. Villages are the locations of groups of households with cultural and socio-economic characteristics. Animal agents represent animal populations and individuals of the ten most hunted species. Animal agents are characterized by population density, home range size, body mass and other traits of each species. The model is driven by a series of sub-models: a land cover change sub-model, a demographic change sub-model, a hunting sub-model, an agriculture sub-model and an animal meta-population dynamics sub-model. These sub-models simulate the main process at stake. The authors evaluated their model with a sensitivity analysis and validated their model using the protocol of Pattern Oriented Modeling (POM). Model results show that the establishment of human activities slowly decreases animal abundance, biodiversity and carbon stocks. Animals have to be hunted further and further and the number of kills decreases. This leads to an increase in cultivated area. The calibrated simulation eventually reaches a stable village size corresponding to field data. Other non-calibrated simulations have more unstable dynamics. Village population size is identified as the most important variable in the model. The sensitivity analysis also shows that the results are robust to the wide ranges of unknown parameters as the model is developed with a rich dataset from field study, remote sensing and literature. This second example, while completely different from the previous example on land-use dynamics in the Pampanga delta in the Philippines, also illustrates the complex dynamics at stake between social and ecological systems. The following section provides more examples on the special case of water resources.

2.3. The special case of Water Resources

Water resources systems form a special case of CHANS and are the focus of hydro-economic modeling and socio-hydrology. Because water is so central to most natural systems, countless models have been developed to study how humans and water interact. Most agent-based and decentralized models developed fall within the three following categories: models of municipal/residential/household water users, river basin models with different types of agents, and models of farmers using water to irrigate their crops which is by far the predominant category and which is investigated in more details in Chapter 3. These models are usually coupled with water resources/hydrologic/hydraulic/water balance models. A good example from the first category is given by Galán et al. (2009) in their article describing an agent-based model developed to study domestic water management in the Valladolid area in Spain. The overarching goal of this study is to gain insights into how domestic water demand aggregates to complex spatial and temporal water demand patterns, a key factor for domestic water management. The agents are household water users, and an urban dynamics sub-model simulates the migratory movements of the households based on socioeconomic factors. Another sub-model simulates opinion and technology diffusion in the metropolitan area. A statistical model was created from a water consumption databased and a socioeconomic database to derive water consumption behavioral rules. The authors use three scenarios to study the system dynamics in an exploratory way. The first scenario is a baseline scenario. The second scenario assumes foreign immigration of low wealth agents. The third scenario was developed to study a phenomenon observed empirically in Spanish cities: the non-decrease of prices of unoccupied dwellings in city centers. Model results show that domestic water consumption depends on urban dynamics and the change of the territorial model. City water use can change significantly simply due to families moving from city centers where they have mainly indoor use to the suburbs where they also have non-negligible outdoor water use. Other examples of ABMs applied to domestic water use include the model developed by Athanasiadis et al. (2005) which integrates a social agent-based model of consumers with econometric models to simulate the residential water supply and demand chain, and the framework presented by Shafiee and Zechman (2013) to simulate water distribution contamination events while considering the impacts of water users' behavior.

ABMs used for watershed management generally use optimization to describe agents' behavior. One of the earliest attempts to use ABM to get insights into water resources management for river basins is provided by Schlüter and Pahl-Wostl (2007) in their paper titled "Mechanisms of resilience in common-pool resource management systems: an agent-based model of water use in a river basin". In this paper the authors use the example of the semi-arid Amudarya River Basin to evaluate the usefulness of ABM in assessing system resilience. They built their model with a social subsystem, an irrigation subsystem and an aquatic ecosystem subsystem. Their model shows that when irrigation is the only type of water use in the basin, a centralized system performs better than the decentralized regime. However, when farmers diversify their water use and resort to fishing as a supplementary source of income, the decentralized regime performs better and both the centralized and decentralized regimes become more resilient. Yang et al. (2011) present a multi-agent system to study water management in the Yellow River Basin in China. They use the decentralized optimization for multi-agent systems framework developed by Yang et al. (2009) to understand how the regulation and test plans to improve water management in the Yellow River Basin impact the socioeconomic and environmental systems. They find that regulations decrease water consumption and increase profits at the system level, leaving more water to the downstream ecosystem agents. However, the implementation of a water market decreases water consumption even further and increases total profits. Giuliani and Castelletti (2013) use an ABM to assess the value of cooperation and information exchange in large water resources systems using the Zambezi River Basin as a case study. In their framework, hydro-power plants are modeled as decision-makers and an agent is created to represent the environment's interests. They find that downstream agents can better adapt to upstream agent's behavior in the case of complete information exchange, and that coordination is highly beneficial to the environmental agent.

As agriculture represents 70 to 80 percent of water use worldwide, it is natural that a significant portion of ABMs that have been developed to study CHANS with a focus on water are models of farmers and their interactions with the environment. For example van Oel et al. (2010) developed an ABM to study the feedback mechanisms between water availability and water-use in the Jaguaribe, a semi-arid river basin. The model simulates farmers' decisions on crop types, irrigation source and quantity and irrigated area. The ABM is coupled with a semi-distributed hydrologic model of the river basin. Results show that the model performs well in the depiction of spatial and temporal variability of how water availability influences water-use and vice-versa for the period 1996-2005. The authors also find that changes in water availability have negative impacts during the wet season but positive impacts during the dry season, implying that water use during the wet season might amplify water stress during the dry season. This article illustrates how agriculture is a very powerful link between the human system and the natural system. Ng et al. (2011) present a very different model focusing on water quality impacts of agriculture. The first component of the model is a hydrologic-agronomic model of the Salt Creek watershed in Illinois developed with the Soil and Water Assessment Tool (SWAT). The hydrologic-agronomic component is used to model crop yield and stream nitrate load. The second component is an ABM of farmers' Best Management Practices using economic optimization. Crop yield from the hydrologic-agronomic component is fed to the ABM and farmers' decisions are fed to the hydrologic-agronomic component to calculate stream nitrate load. The model also considers markets for carbon allowances and second-generation biofuel crops. The ABM includes complex individual behavior through Bayesian learning, stochastic optimization, the use of forecasts by farmers and the inclusion of interactions between farmers. The results show that farmers tend to be cautious and that crop prices, production costs and yields are the most important drivers of farmers' decision-making. The authors suggest the use of interviews and role-playing games with real farmers to develop better empirical models of farmers' behavior. This is a methodology that was adopted by Gurung et al. (2006) in their paper on the use of companion modeling for conflict resolution and institution building in the Lingmuteychu watershed in Bhutan. In this exemplary article, the authors describe how they helped resolve a conflict between seven villages over shared water resources by helping stakeholders to reach an agreement and to create an institution using the companion modeling approach with a multi-agent system and role-playing games. In a first step, the stakeholders were asked to play role-playing games. The games were used both to inform the farmers about alternative scenarios and practices and to develop rules for their behavior and decisions. The second step consisted in developing a multi-agent model including water balance and land-use using the behavioral rules developed through the role-playing games. The model was used to study 36 scenarios with different strategies for resource use and their impacts on the environment and the economics of the villages. Additional workshops and role-playing games were held after the model results were obtained. The authors explain that a role-playing game has to be designed to be "playable" but also provide a good test of model realism, as the players can validate or invalidate the behavioral rules, actions and the structure of the game. They also indicate that the game and the model are merely mediation tools and they cannot and should not be used as expert resources on technical development. This article shows how companion modeling is a very specific but very powerful use of ABM to promote stakeholder discussion and conflict resolution. Finally, a more theoretical article by Berger and Troost (2014) discusses the use of ABM to develop climate change mitigation and adaptation options in agriculture. They indicate three fields of application: land-use change and supply response, stress-testing of adaptation strategies, and ex-ante policy analysis. They emphasize the flexibility of multi-agent systems to simulate agricultural systems at various scales, from the singe-farm scale to the regional and global scales.

All these models illustrate the usefulness of ABM to study CHANS and show the width and diversity of ABM applications in the field. The last section of this chapter discusses the challenges and opportunities of ABM.

2.4. Challenges and Opportunities

Filatova et al. (2013) identify four methodological challenges for spatial agent-based models of socio-ecological systems: design and parameterizing of ABMs; verification, validation and sensitivity analysis; integration of socio-demographic, ecological and biophysical models; and spatial representations. These four challenges are in essence the same for agent-based models of coupled human and natural systems with the exception of the third one which could include the integration of economic, hydrologic and agricultural models. Some of these challenges are common to any ABM exercise and others are more specific to ABMs applied to CHANS. Crooks et al. (2008) find seven challenges in agent-based modeling of geo-spatial simulations. These challenges are: "*the purpose for which the model is built, the extent to which the model is rooted in independent theory, the extent to which the model can be replicated, the ways the model might be verified, calibrated and validated, the way model dynamics are represented in terms of agent interactions, the extent to which the model is operational, and the way the model can be communicated and shared with others*". Some of these challenges overlap with the ones suggested by Filatova et al. (2013) while others like the last one complete the list. This section offers a review of these challenges as well as an overview of the opportunities offered by ABM.

The first challenge generally faced by agent-based modelers relates to the design and parameterization of the model. Depending on the type of agent being modeled, the purpose of the model, the scale of the system studied, the scientific field of the modeler and the computational capacity available, there are countless ways to design an ABM. As an example, An (2012) finds nine different behavioral models used to represent humans in ABMs of CHANS and she emphasizes that these models range from highly empirical ones to mechanistic and process-based ones. Her article illustrates the complexity and lack of consensus on modeling human behavior and designing ABMs. Indeed, there are a wide range of methods to derive agents' behavior, from using empirical rules such as in the "companion modeling" approach or using statistics or econometrics, to using behavioral theories from social sciences and psychology. Kelly et al. (2013) also mention that parameterizing a model is often challenging because of the detailed information necessary to model the complex interactions between agents, sometimes forcing reduced spatial scales for the models.

The second challenge, verification, validation and sensitivity analysis, is a challenge for every agent-based modeler and is not limited to CHANS. For general discussions on validation of ABMs, see Bharathy and Silverman (2010), and Xiang et al. (2005). Filatova et al. (2013) and An (2012) agree that the high number of model parameters due to micro-level modeling makes ABMs very hard to validate, especially through sensitivity analysis (An, 2012; Filatova et al., 2013). Windrum et al. (2007) identify three methods for validating agent-based economics: indirect calibration, the Werker-Brenner calibration approach and the history-friendly approach. These methods are very specific to models focusing on economics and the authors make the assumption that econometrics is the most appropriate way to validate empirical ABMs. Moss (2008) however argues that econometrics represents one end of the validation methods spectrum and he promotes the use of companion modeling which is at the other end of this spectrum. In the companion modeling approach, the modelers engage directly with the stakeholders they are modeling the behavior of in order to validate their model. See the book *Companion Modelling* by Étienne (2011) for an in-depth review of the subject. Ligtenberg et al. (2010) discuss the validation of agent-based models for spatial planning using role-playing games, an approach similar to the one used in companion modeling. They present a specific validation method and apply it to a case study of students allocating land use for a region in the Land van Maas en Waal region in the Netherlands. The agent-based model developed for this case study provided a controlled environment that helped understand how to represent agents' beliefs and preferences. The approach was too simplistic but showed that role-playing games are a very promising tool to validate agent-based models of spatial planning. Another approach of agent-based modeling that incorporates validation from the beginning is the so called "Pattern-Oriented Modeling". Pattern-oriented modeling is described by Grimm and Railsback (2012) and its use for ABMs is described by Grimm et al. (2005). In this framework models are designed and calibrated based on patterns identified in the real world. The first step usually consists in finding the most characteristic patterns of a system at different scales. Following this, the model is designed and then calibrated to reproduce these patterns as accurately as possible. Pattern-Oriented is particular in the sense that it is an integrated framework that provides guidelines to both design and calibrate or validate a model in order to understand how patterns emerge in a complex system.

The third challenge is integrating different models. When studying CHANS, one must usually integrate knowledge and therefore models from different disciplines such as economics, ecology, hydrology, sociology, etc. The vision of Integrated Environmental Modeling is described by Laniak et al. (2013). One of the main challenges of integrating models from different disciplines is that these models have different spatial and temporal scales causing the integration to be technically difficult to implement according to Parker et al. (2002). For example, these scale issues make it hard to match boundaries of hydrologic systems and socio-economic systems. They also make uncertainty and error estimations more challenging.

Two other significant challenges are spatial representation and communication of these models. Spatial representation also relates to the different scales of CHANS and the way these different scales can be incorporated in models. Furthermore, this relates to the representation of spatial heterogeneity and landscapes (Filatova et al., 2013). The question of how to communicate and share ABMs remains a challenge for the different agent-based modeling communities, although efforts have been made in the recent years to develop universal frameworks to describe ABMs. Grimm et al. (2010) provide a review of the Overview, Design concepts and Details (ODD) framework as well as a first update of the framework. The ODD protocol is the most popular way of describing ABMs to date and has been updated several times since its creation in 2006. The protocol suggests presenting all ABMs following seven key elements: (1) Purpose, (2) Entities, state variables and scales, (3) Process overview and scheduling, (4) Design concepts, (5) Initialization, (6) Input data, and (7) Sub-models. The first three elements are part of the Overview principle, the fourth is the Design concepts principle, and the last three elements are part of the Details principle. The ODD protocol has been upgraded to the ODD+D protocol by Müller et al. (2013) to better account for human decisions. The ODD+D includes 51 questions, the answers to which help describe ABMs with human decisions in depth. A comprehensive review of standardized model descriptions for agent-based models of coupled human and natural systems is presented by Müller et al.

(2014). The authors show the challenges of having universal standards for describing ABMs and they show how the current diversity of model description is due to the variety of purposes for describing models.

2.5. Conclusion

There is a wide variety and diversity of ABMs that have been developed to study CHANS. Some models focus on social-ecological systems, others focus on hydrologic-economics models, but all combine a model of the environment and a model of human behavior. The literature also includes many models focusing on water and water resources, especially in the context of agriculture and farming. While the approach is very promising and is described as one of the ways forward by many authors, there is still a number of challenges that need to be overcome. The main challenges are the verification and validation of these models and the use of sensitivity analyses. Another challenge is the integration of different models from different disciplines such as economics, ecology, social sciences, psychology, hydrology or agriculture. Other challenges include the spatial representation of these models and the integration of different spatial and temporal scales, and finally the communication of these models and the enabling of model sharing and model reproduction.

CHAPTER 3

ASSESSING THE IMPORTANCE OF INDIVIDUALS IN MODELING COUPLED HUMAN AND NATURAL SYSTEMS

3.1. Introduction

Climate change, deforestation, the disappearing of entire lakes and seas and other large-scale environmental issues, such as the hypoxia zone in the Gulf of Mexico, demonstrate that the Earth has moved into the Anthropocene: an age where humans are the main driver of environmental and ecological changes. This realization has prompted scientists to create a new form of science: the science of coupled human and natural systems (CHANS). This science has been growing steadily over the past 15 years (Liu et al., 2007b; Alberti et al., 2011) and advocates for the integrated assessment of human and environmental systems. There have also been a number of frameworks and sub-fields that have emerged in this area to study specific CHANS such as socio-hydrology (Sivapalan et al., 2012), coupled social-ecological systems (Schlüter et al., 2012), hydro-economic systems (Harou et al., 2009), integrated environmental modeling (Laniak et al., 2013) and others. The science of CHANS and its sub-fields call for interdisciplinary collaboration and systematic modelling of both the human and the natural systems to reveal the complex dynamics at stake in such systems.

3.1.1. Modeling Coupled Human and Natural Systems

Models of CHANS are often called "Integrated Models" as they are designed to integrate both human and environmental dynamics in order to provide holistic solutions to complex problems (Laniak et al., 2013). In the past few decades, environmental models have become increasingly complex due to improving computing power and improving quality of data, both spatially and temporally. The Geographical Information Systems (GIS) revolution played a particularly important role in the development of increasingly detailed distributed environmental models (Karimi and Houston, 1996). The inclusion of the human component in environmental models has been much more recent and the field is still in its infancy. While progress has been made and new tools have been adopted to develop more integrated environmental models (Kelly et al., 2013), there is still much work to be done to properly represent human behavior and human influence in these models (An, 2012). Yet, developing more complex models of humans and their behavior within natural systems is very challenging. One of the main challenges is the validation of such models due to the lack of data on and understanding of human behavior (An, 2012; Ligtenberg et al., 2010). In following the advice of Axelrod (1997) to "Keep it Simple, Stupid" (KISS), many researchers have been slow to incorporate more complex human behavior. This simplified approach, however, is beginning to be challenged (Terano, 2008). Models of humans and their behavior have been kept simple as little is known on the effects of having more complex models and if the added complexity plays any significant role in the system. Indeed, very few studies have systematically evaluated the impacts of complex human behavior on CHANS (Huang et al., 2013).

3.1.2. Agent-Based Modeling applied to CHANS

While it is generally easy to decide what model to use for the natural system, there is no consensus on what model to use for the human system. Various tools have been developed in social sciences (Lave and March, 1993), economics (Tesfatsion, 2003), psychology (Gluck and Pew, 2006) and other fields but no model has been universally accepted across all disciplines as the best way to model human behavior. One modeling approach however has been regularly cited as particularly effective for CHANS: agent-based modeling (ABM). An (2012) provides a review of agent-based models used to model human decisions in CHANS. She identified 121 publications applying ABM to CHANS as of 2011, mainly in the fields of ecology and geography. Kelly et al. (2013) identified ABM as one of the five most common approaches used for integrated environmental assessment and management. They explicitly mention that "*ABMs are sometimes developed and applied to incorporate complex cognitive representations of individuals' mental models, behaviors and choices […]. Thanks to such features, ABMs can explore, for example, how the attitudes of individuals or the institutional setting can affect system-level outcomes*". In the field of social-ecological systems the use of ABMs are particularly prevalent, as illustrated by Rounsevell et al. (2012), Schlüter et al. (2012) and Filatova et al. (2013).

Moreover, ABM has also been used to study agricultural and water resources systems, two categories into which the model presented in this work falls. ABMs have been used to model different types of water users, from domestic users to irrigators. Athanasiadis et al. (2005) and Galán et al. (2009) use ABM to simulate the behavior of residential water users. In a review of urban water demand as CHANS, House-Peters and Chang (2011) identify ABM as a promising modelling approach for future research. Schlüter and Pahl-Wostl (2007) describe one of the earliest attempts to use ABM to study CHANS at the scale of a river basin. Yang et al. (2009; 2011) also present a framework to use ABM to study watershed management and apply their framework to water allocation management in the Yellow River Basin. They model irrigators as agents and use their model to study the resilience of the system to variability and uncertainty of water availability. Similarly, van Oel et al. (2010) developed an ABM to study feedbacks between water availability and water use in a river basin. Their ABM is used to model farmers' decisions over land and water use and is coupled with a water balance model. More recently, Arnold et al. used an ABM to simulate the decisions of farmers on farm production plan – including irrigation – and coupled it to a hydrological-balance model to quantify the economic importance of irrigation water reuse (Arnold et al., 2014). These studies show that ABM is considered a promising, and in some fields well-established, tool to study the interactions between humans and their environment, especially when this environment includes a hydrologic system.

3.1.3. Context and motivation

This study is an attempt to answer a seemingly simple but, in fact, sophisticated question: Do individuals matter in modeling CHANS? In other words, the purpose of this work is to understand if including individuals and their behavior in models of CHANS improves the models and offers more insights into the dynamics of the systems. As it is often hard to decide how complex and detailed a model should be, especially when it comes to modeling a system driven by human behavior, this work aims at illustrating the benefits of modeling the human system at the individual level. We plan to demonstrate these benefits by representing individual farmers who are using groundwater to irrigate cash crops in the

High Plains Aquifer region, where complex interactions between irrigators and their environment have shaped the economics and the hydrology of the region. Decades of intensive groundwater irrigation for cash crop agriculture have depleted both groundwater and surface water in many regions of the aquifer, causing conflicts and concerns over the sustainability of agriculture in the area (Steward et al., 2013; Scanlon et al., 2012). In our framework, farmers and institutions form the human component of the system and rivers and the aquifer form the natural component of the system. In order to determine if individuals – in this case, the farmers – and their behavior matter in such a system, an integrated model was developed. The model incorporates an agent-based model of farmers' irrigation behavior and a groundwater model. Based on current literature (see sections 1.1. and 1.2.), agent-based modeling appeared to be the most appropriate framework to study a hydrologic-agricultural system driven by individual behavior.

3.1.4. Related work

This work can be related to four recent studies that share a similar context and modeling approach as this work. Three of these four studies focus on regions located in the High Plains Aquifer area and all four studies focus on irrigation and how it connects agriculture, economics and groundwater. Bulatewicz et al. (2010) used the Open Modeling Interface to integrate models of agriculture, economics and groundwater and applied their methodology to Sheridan County in Kansas located above the High Plains Aquifer. Their work highlights the benefits of integrating different models together, while also providing very interesting insights on the interactions between groundwater, yield, farmers' profit and policy, as well as shows the emergence of spatial patterns. Our model extends their work by also modeling individual farmers and their behavior and assessing their impact on the overall system.

Condon and Maxwell (2014) present an integrated hydrologic model used to study the spatial and temporal patterns caused by feedbacks between irrigation and water availability. They apply their model to the Little Washita Basin in Southwestern Oklahoma, USA with an 80-year simulation and perform a scenario analysis. They find that streamflow declines regionally while evapotranspiration increases, amplifying the natural seasons and decreasing the impacts of long-term cycles. They emphasize the importance of physical heterogeneity, a claim that is also made in this paper. Overall, their work focuses on physical characteristics of the feedbacks within the system and on spatial and temporal patterns without analyzing the role of individuals and their behavior.

Foster et al. (2014) introduce a new modeling approach of irrigation behavior in groundwater systems. Their modeling approach incorporates the impacts of well yield and climate on crop production and water use to determine irrigation demand. Their model is applied to a case study in the Texas High Plains region and shows that changes in groundwater availability causes irrigation behavior to display complex nonlinear responses due to declining well yield. Their work is related to the work presented in this article as they specifically address the issue of modeling farmer's behavior. However, they do not characterize the importance of individual farmers and their behavior in the dynamics of coupled agricultural and hydrologic systems and instead focus on the theoretical or general behavior of farmers.

Mulligan et al. (2014) present a model which is very similar to the model presented in this article as it couples an agent-based model of farmers' irrigation behavior with a groundwater model to study a subwatershed of the Republican River Basin, the basin studied in this paper. They use their model to assess different groundwater policies and evaluate how these policies perform with a realistic representation of decentralized heterogeneous farmers as opposed to farmers following a centralized decision-maker. They show that it is crucial to model farmers as decentralized and heterogeneous entities when assessing groundwater policies. However, they do not specifically assess the effects of representing individuals and they aggregate farmers to simplify their model.

Although we share a similar modeling approach or have a similar study area as these four studies, this study is unique in that we assess the importance of individuals and their behavior in modeling CHANS. Our approach is more similar to the approach of Huang et al. (2013) as they assess the effects of agent heterogeneity in the presence of a land-market, but the general context is different as we focus on water resources rather than land-use and individual heterogeneity rather than physical heterogeneity.

Our model is presented in section 3.2 and its application to a region located in the Republican River Basin is presented in section 3.3. Additional discussion on the importance of individuals in CHANS is provided in section 3.4.

3.2. Methodology

3.2.1. Structure of the model

The integrated model that we developed to understand the role of modeling individuals in CHANS has two main components. The first component is an ABM that simulates farmers' daily decisions on irrigation and annual decisions on land surface devoted to irrigated agriculture, and annual decisions of a regulatory agency on regulations. The second component is a groundwater model that simulates groundwater flow in the underlying aquifer and stream-aquifer interactions. Figure 1 shows the general organization of the model. The human and the hydrologic models are coupled together through pumping decisions and water-table in the aquifer. The agent-based model is subject to external macro-economic drivers such as fuel and corn prices and both models are subject to external climate drivers such as precipitation and evapotranspiration. Coupled together, the two models are able to simulate the co-evolution of the human and natural systems over long periods of time. Figure 2 shows the flow chart of the complete model.

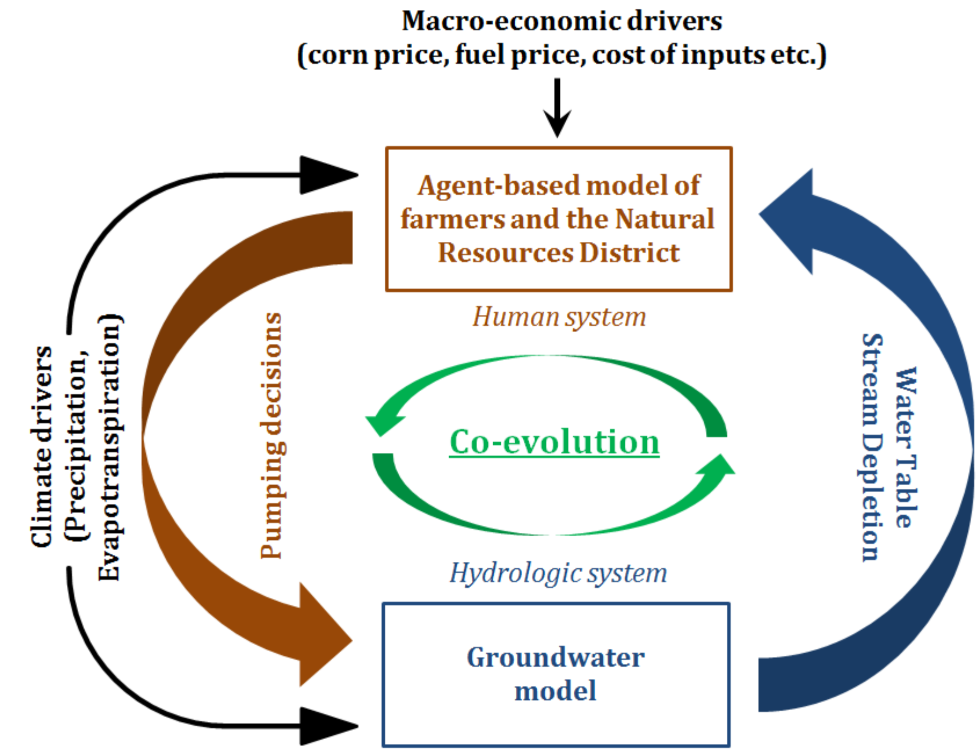

Figure 1: Diagram of the integrated model

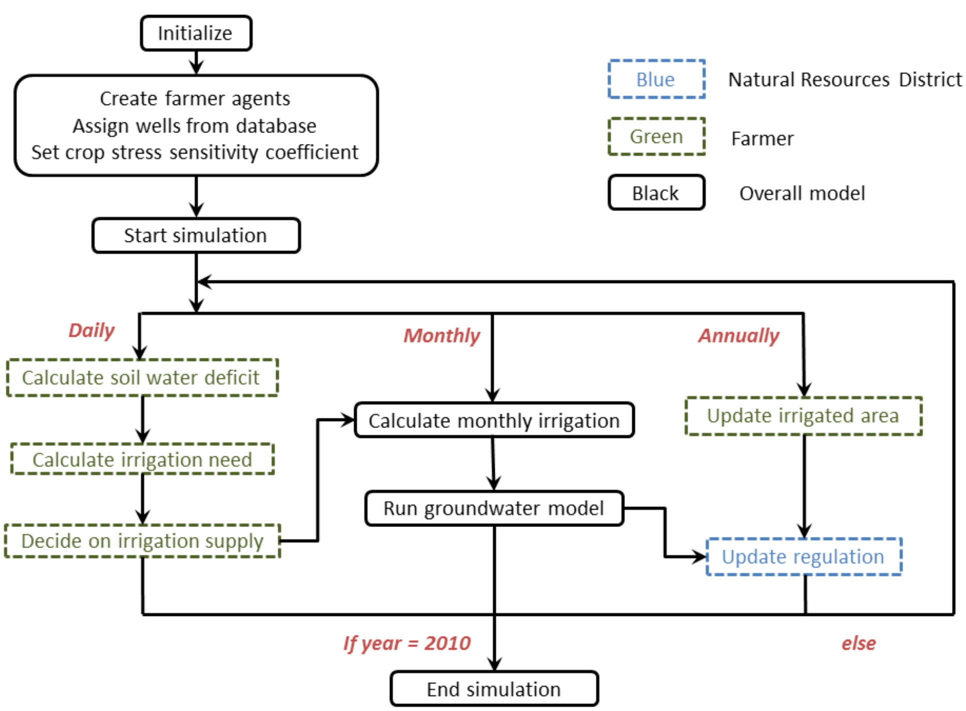

Figure 2: Flow Chart of the integrated model

Every day, farmers make decisions on the amount of irrigation to apply on their fields based on soil water deficit. These daily pumping decisions are aggregated monthly and used as input for the groundwater model. The groundwater model is run every month and provides updated water-table and baseflow values to the ABM. Every year, the regulatory agent makes decisions on irrigation regulations based on streamflow depletion. Every year, farmers also make decisions on their irrigated surface based on long-term potential and actual evapotranspiration. The model is initialized and then runs at a daily time step with actions performed at the daily, monthly and annual time steps. The groundwater model is run at a monthly time step as it is the bottleneck in terms of computation time. This time scale still allows the model to capture the water-table drop during the growing season. Both models are described in more details in the next two sections.

3.2.2. The agent-based model

There are two types of agents in this model: farmers and one regulatory agency – the Natural Resources District (NRD) in Nebraska, the location of the case study. The NRD agent sets historical regulations when the flux of water from the aquifer to the streams – used as a proxy for baseflow – drops under some thresholds. These thresholds were calibrated to ensure that each new regulation in the model is approximately implemented on the year when it was implemented in the NRD in Nebraska (see presentation of the case study in section 3.1). Each regulation is a cap on the annual amount of irrigation withdrawals imposed on all farmers. Farmers make decisions on daily irrigation and annual land surface devoted to irrigation. The framework used for the farmers to decide on daily irrigation was the soil water balance approach. This approach was developed by the Food and Agriculture Organization (FAO) in its seminal paper on crop evapotranspiration (Allen et al., 1998). Each day, the farmers calculate soil water deficit at each of their field and use this value to decide if and how much to irrigate. Farmers may own several wells and each well is associated with a separate field. Many irrigation scheduling and water management approaches provided to farmers rely on this soil water balance method (Rhoads and Yonts, 1991; Lamm et al.; Andales et al., 2011). In practice, farmers can also visually assess soil moisture or use soil moisture sensors to determine soil water deficit and make a decision on irrigation timing and amount (Hanson et al., 2000). Foster et al. (2014) recommends using such intra-annual methodology to model farmers' behavior regarding irrigation as opposed to simulating farmers' behavior at an annual time-step. The soil water balance is calculated based on water deficit from the previous day, daily potential evapotranspiration and daily precipitation. It relies on parameters describing the quality of the soils, crop growth and crop water stress. After daily irrigation demand is calculated, farmers calculate daily irrigation supply for each active well. Supply is restricted by well yield and the annual irrigation cap. Farmers' behavior is also differentiated through the introduction of a coefficient characterizing their sensitivity to crop stress called SC, following the work of Miro (2012). This coefficient is used to modify farmers' Managed Allowed Depletion (MAD) recommended values are usually provided for each stage of a crop growth season. Equation (1) shows where SC is introduced in the irrigation calculation process.

$$d_{MAD} = \frac{MAD}{100} \times TAW * SC \quad (1)$$

MAD is the Managed Allowed Depletion in percentage, TAW is the Total Available Water in the soil and d_{MAD} is the depth of allowed depletion in inches. Corn yield is then computed at the end of the growing season based on maximum corn yield and potential and actual crop evapotranspiration during six crop growth stages following Jensen (1968). Annual profit is calculated using corn yield, corn price and input costs – fertilizer, pesticide, pumping cost etc. Farmers' annual decisions on irrigated area are modeled based on the ratio between actual and potential crop evapotranspiration averaged over three years (Rosegrant et al., 2002). Each year, farmers decide if they should reduce their irrigated acreage or use all the available land depending on the long term water-deficit in their fields. The model is described more comprehensively in Appendix A following the Overview, Design concepts and Details and human Decision-making (ODD + D) protocol, a standardized protocol for the description of agent-based models with human decisions (Grimm et al., 2010; Müller et al., 2013).

3.2.3. The groundwater model

The groundwater model was developed with MODFLOW 2000 (Harbaugh et al., 2000). MODFLOW uses the finite-difference method to solve the three-dimensional groundwater flow equation for a porous medium. It is a fully distributed numerical program designed for high modularity. The development of the groundwater model depends on the case study. Here, the model was developed to simulate groundwater flow in a region within the Republican River Basin (see section 3.1. for the description of the case study). All the data used to develop the model was extracted from the Republican River Compact Administration (RRCA) model (RRCA, 2003). Data extracted from the RRCA model includes the top and bottom layers of the aquifer, aquifer properties such as hydraulic conductivity and storativity, stream location and properties and monthly evapotranspiration. Other time-varying inputs to the model include recharge and pumping rates at wells, both of which are monthly outputs from the ABM. Boundary conditions were created arbitrarily based on water-levels in the pre-development period calculated in the RRCA model. While the RRCA model is a calibrated model, the groundwater model we developed was not calibrated as the shape and size of the chosen location do not allow an easy calibration of the model. The model simply allowed us to simulate spatially distributed impacts of pumping on water head and baseflow for an exploratory analysis. However, the results from the groundwater model are consistent and realistic as shown by the comparison of simulated water-table in 2009 against data from fifteen USGS wells spread across the region. Overall, the model over-predicts water table in 2009 by 9 feet due to the fixed boundary conditions. In reality, water head at these boundaries also drops because of groundwater pumping. The root-mean-square deviation is 37.4 feet and the coefficient of variation of the root-mean-square deviation is 0.49 which is acceptable considering the large uncertainty present in both the data and the model itself.

3.3. Application to the Republican River Basin

3.3.1. Case study

The Republican River Basin is shared by the states of Colorado, Kansas and Nebraska. It is a 24,900 square miles basin located above the High Plains Aquifer, one of the largest aquifers in the world. In the Republican River area, the aquifer is supported by shallow alluvium and deeper bedrock formations. The economy of the basin is dominated by agriculture and corn is the predominant crop grown in the area. Most of the 8.5 million acres dedicated to agriculture in the region are irrigated by the nearly 100,000 registered active wells within the basin (Nebraska Department of Agriculture, 2013). Because of this intensive irrigation, the basin suffers from both groundwater and streamflow depletion. In 1942 the three States signed the Republican River Compact to divide surface water in a fair way. However, over-pumping of the aquifer eventually led to streamflow depletion, a more visible issue that triggered a conflict between Kansas and its two neighbors. Kansas accused Nebraska and Colorado of violating the Republican River Compact and after bringing the complaint to the Supreme Court a final settlement was eventually reached in 2002. In Nebraska, Natural Resources Districts are responsible for the integrated management of ground water and surface water. Providing local governance, they implement groundwater regulations for irrigation wells. Two Natural Resources Districts are present in the case study region: the Middle Republican Natural Resources District and the Upper Republican Natural Resources District (Nebraska Association of Resources Districts, 2014). For simplicity and because more data was available, only the Upper Republican Natural Resources District was considered in the model.

The region chosen for this case study is a 2,500 square-mile area roughly overlapping the counties of Chase, Hayes, Dundy and Hitchcock in Nebraska. These four counties are located in southeastern Nebraska and share borders with Colorado and Kansas. The region receives an average of 20 inches of precipitation annually. Figure 3 shows the location of the area of study, along with the streams, wells and climate stations used in the model. There are about 2,200 registered irrigation wells in the area. The colors indicate how many acres can be irrigated by each well. The well database from the Nebraska Department of Natural Resources also includes data such as well yield, year of activation of the well, irrigated acres, etc. The sources for all the different datasets used to build the case study are presented in Table 1.

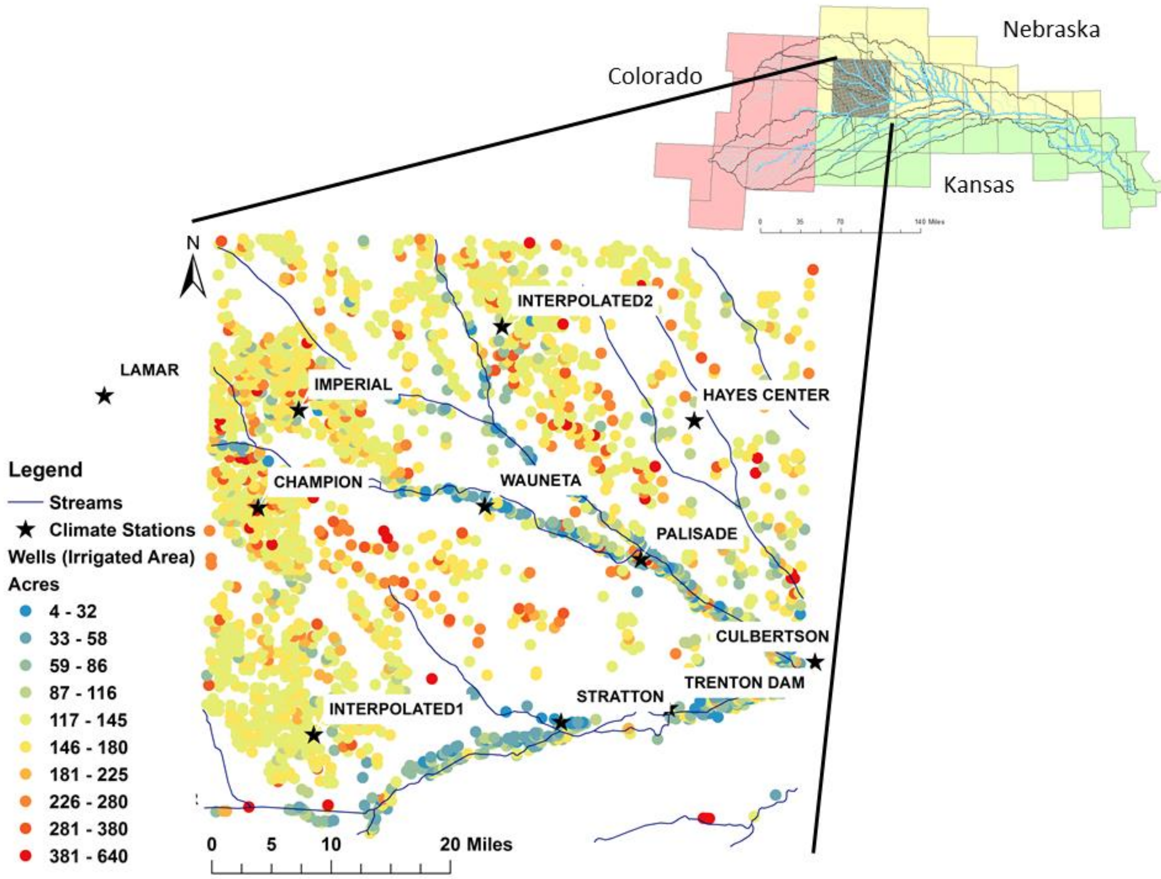

Figure 3: Area of study in the Republican River Basin

Table 1: Datasets used in the integrated model

Dataset	Model parameters and variables	Source	Link
Soil type	Available water capacity	*STATSGO, Nebraska*	http://water.usgs.gov/GIS/metadata/usgswrd/XML/ussoils.xml
Well inventory	Well location, Maximum well yield, Irrigated acres, Well activation date	*Nebraska Department of Natural Resources*	http://dnr.nebraska.gov/gwr/registered-groundwater-wells-data-retrieval
Crop growth	Depth or rooting zone, Crop coefficient, Management allowed depletion	*Andales et al., 2011*	
Climate	Daily Precipitation, Daily Potential Evapotranspiration	*High Plains Regional Climate Center*	http://www.hprcc.unl.edu/index.php
Costs	Corn prices	*Farmdoc, University of Illinois Extension*	http://www.farmdoc.illinois.edu/manage/uspricehistory/us_price_history.html
	Diesel prices	*U.S. Energy Information Administration*	www.eia.gov/ae
	Other costs (fertilizers, pesticides, labor etc.)	*Texas AgriLife Extension Service*	http://agrilifeextension.tamu.edu
Groundwater	Top and ottom elevation, Hydraulic conductivity, storativity, Monthly ET, Stream network, Initial head	*Republican River Compact Administration (RRCA)*	http://www.republicanrivercompact.org/index.html
Regulations	Regulations	*Nebraska's Natural Resources Districts*	http://nrdnet.org/water.php

The scale of the region was chosen so to be small enough to model every individual farmer, yet large enough for feedbacks to occur between the human system and the natural system. Figure 4 shows the increase in irrigated surface in the region along with the decrease of annual streamflow a few miles downstream of the outlet of the region. This illustrates the challenges faced by stakeholders in the region in terms of human development and its related environmental impacts and shows the main motivation for choosing this case study. Furthermore, Figure 4 demonstrates how humans and the environment have been co-evolving over the past hundred years in this portion of the Republican River. The issue of groundwater-fed agriculture in the High Plains, as well as local streamflow and groundwater depletion, which it is intricately linked with, is crucial to the food security of the US. One of the motivations behind this work is to provide better models to tackle this issue of sustainable groundwater-fed irrigation by recognizing the importance of individual behavior in human-environment interactions.

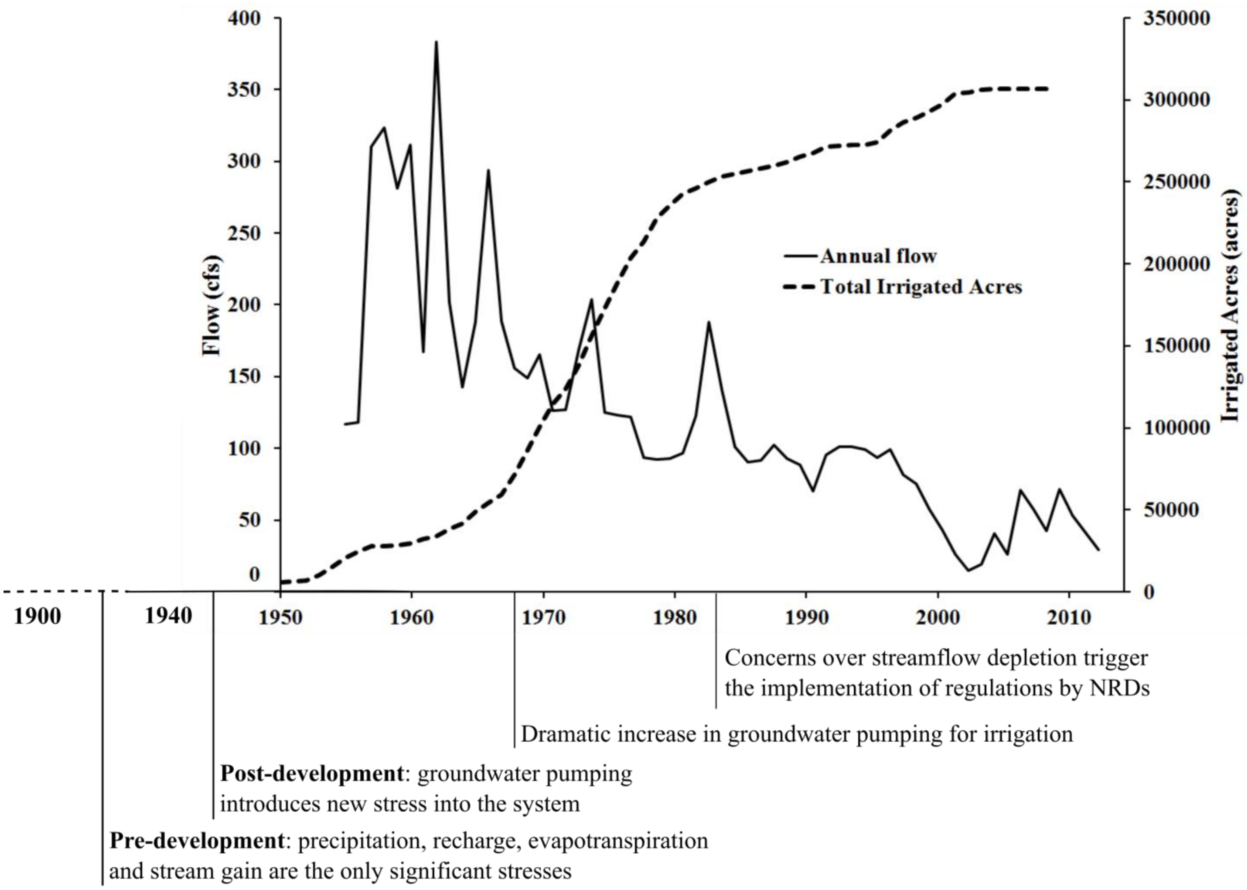

Figure 4: History of irrigation and streamflow in the region

In the ABM, farmers were created by dividing the 2,500 square mile study area into a grid of 1 square-mile squares and assigning a farmer to each square containing one or more wells. The average farm size in Nebraska is 972 acres (Nebraska Department of Agriculture, 2013) which is 1.5 times the size of a farm in the model – 650 acres. With this assumption, 1040 farmers were incorporated in the model. Farmers that do not operate wells were not considered in the model as it is assumed they do not have significant impacts on the environmental system. For simplicity, it was assumed that corn is the only crop grown by farmers. Corn represents the predominant crop grown in Nebraska accounting for 57% of the total cropland (United States Department of Agriculture, 2013). The next section shows how well the model performs in terms of predicting corn yield in the region.

3.3.2. Validation of the model

While this model is used in an exploratory way to study the importance of individuals in CHANS, it is important to demonstrate that the results obtained with this model are realistic. In this case, the ideal would be to validate the model against irrigation data. However, irrigation data is usually hard to obtain, especially in the Republican River Basin because of on-going lawsuits and conflicts (Popelka, 2004) and because farmers are not required to document their water-use (Szilagyi, 1999). As a qualitative validation, the University of Nebraska Crop Watch page on Irrigation and Water Management for Corn indicates that the average irrigation need for corn in western Nebraska is 14 inches, while the long-term average irrigation predicted by our model over the region is 14.1 inches (Irrigation and Water Management for Corn). However, there are other variables that can be used to meaningfully validate and calibrate the model. The most reliable data that we found for validation was USDA county-level historical corn yields, which were available for the entire simulation period for the four counties in the region. Corn yield calculation depends on other variables of the model and especially on irrigation and therefore provides a good assessment of the overall model performances. The average reported corn yield for the region during the simulation period is 119.7 bushels per acre while the average simulated corn yield is 120.9 bushels per acre. This shows that the model is good at predicting mean corn yield in the region when averaged over a long time-period. The root-mean-square deviation is 23.5 bushels per acre over the 60 years of the simulation and the coefficient of variation of the root-mean-square deviation is 0.2. Both of these values are really low, showing that the model performs well in terms of determining the regionally-averaged corn yield. Most of the deviation between historical and predicted corn yield derives from processes that are not captured by the model such as crop damages from flooding. For example, the model predicts a high average corn yield of 206 bushels per acre in 1993 because of high precipitation whereas yields were actually really low in the region (average of 108.5 bushels per acre) due to the Great Flood of 1993 and the related crop damages (Perry and Combs, 1998).

3.3.3. Assessing the role of individuals in the system

In order to understand the role of individuals in CHANS, the first step is to assess the impacts of individuals at the system level. Individuals are described by all the parameters that characterize their behavior. In this specific case, the individuals are farmers and they are described by all the parameters that are unique to their behavior regarding irrigation. These parameters describing farmers' behavior can be physical (e.g. well yield, soil type) or personal, psychological or social (e.g. farmers' preferences regarding crop stress). To assess the importance of individuals, a set of simulations were performed where the heterogeneity for each parameter related to a farmer's behavior was turned on and off. When a parameter's heterogeneity was off, all the farmers were assigned the average value for this parameter. These parameters include the maximum irrigated area for each well, well yield, soil type and climate (namely, precipitation and evapotranspiration). It also includes the parameter accounting for farmers' personal behavior SC called "Sensitivity to crop stress" which is used to diversify farmers' attitude toward crop water stress. In one of these simulations, this parameter is heterogeneous and follows a normal distribution with a mean of 1 and a standard deviation of 0.01. The result is a series of 17 simulations going from no individual heterogeneity – all farmers are behaving exactly the same way – to full individual heterogeneity where each individual's behavior is uniquely characterized by the set of parameters. The heterogeneity of the sensitivity to crop stress is turned off in the first 16 simulations where all possible combinations between the four physical parameters are simulated. Simulation 1 has all parameters' heterogeneity off and simulation 16 has all parameters' heterogeneity on. Simulation 17 is similar to simulation 16 with the addition of heterogeneity in farmers' sensitivity to crop stress. This heterogeneity of farmers' personal behavior was treated separately because it was created using a normal distribution contrary to the other physical parameters for which heterogeneity was based on data.

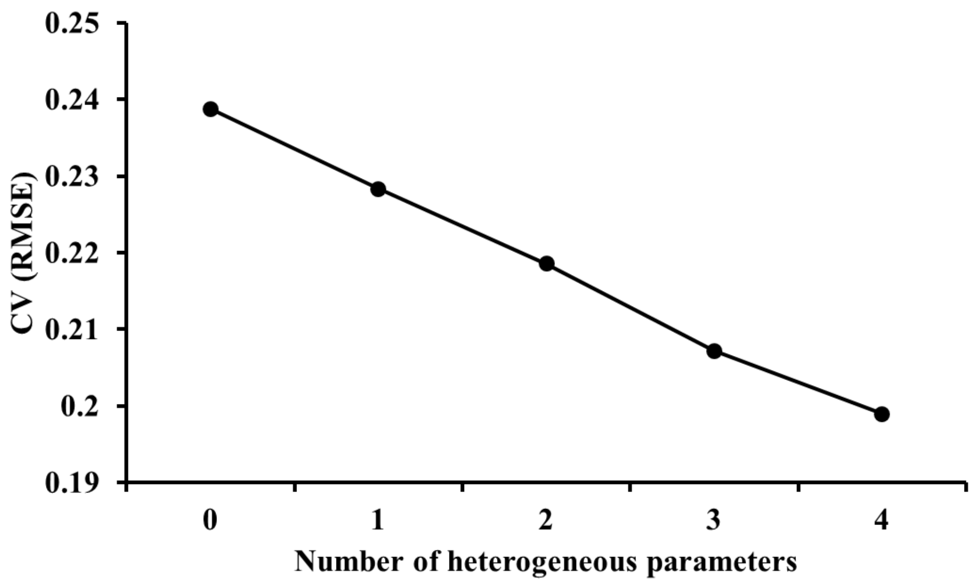

Figure 5: Coefficient of variation of the root-mean-square deviation as a function of the number of heterogeneous parameters

Figure 5 summarizes the results from the first 16 simulations. This figure shows the coefficient of variation of the root-mean-square deviation of simulated corn yield compared to historical corn yield for the period from 1950 to 2005. This coefficient of variation is plotted as a function of the number of heterogeneous parameters. Simulation 1 is the only simulation without heterogeneous parameters. Simulation 16 is the only simulation with all four parameters being heterogeneous. There are respectively four, six and four simulations with one, two and three heterogeneous parameters. Figure 5 presents a striking result: the coefficient of variation of the root-mean-square deviation between simulated and historical corn yield decreases almost perfectly linearly with an increasing number of heterogeneous parameters. In other words, the more heterogeneity is included in farmers' irrigation behavior, the better the model predicts average corn yield in the area of study. To better understand how this behavioral heterogeneity impacts the system, maps of annual irrigation for four of the simulations for the year 2004 are presented on Figure 6. These maps illustrate how individual heterogeneity and spatial variability are related. Since all farmers have the same behavior in simulation 1, they all have the same annual water use for irrigation. On the contrary, simulation 17, the simulation with the most complete depiction of individual behavior, shows more realistic and complex spatial patterns. In particular, simulation 17 not only shows patterns and clusters but it also shows within-cluster variability due to the inclusion of heterogeneity of farmers' personal preferences over crop stress. The importance of this psychological, social or personal component of farmer's behavior is analyzed in more depth in section 4.2. The maps for simulations 2 and 3 show the patterns attributed solely to climate heterogeneity and soil type heterogeneity, respectively. These maps show how the heterogeneity of each parameter reveals different spatial patterns and how incorporating all the real-world individual heterogeneity together leads to the emergence of complex spatial patterns. To complete the picture, Figure 7 shows how spatial and temporal patterns emerge when individual behavior is incorporated in the model. Figure 7 presents a map of corn yield at the end of each decade of simulation 16. The first obvious pattern is the adoption of center-pivot irrigation in the basin from 1950 to 2009. The second pattern, also temporal, is the increase of maximum yield with time due to improved technology and agricultural practices. The third pattern is the spatial variability of corn yield for each year and how these spatial patterns also change with time. Each year the spatial patterns change and the zones of high yield and low yield seem to move around with time. One area located in the top-left section of the region constantly has the highest corn yield from 1950 to 2009. Figure 7 reveals emerging patterns and the many insights that can be gained about the system when accounting for individual behavior at the system level. These results can be compared to results described by Condon and Maxwell (2014), where the emphasis is on the natural system rather than the human system.

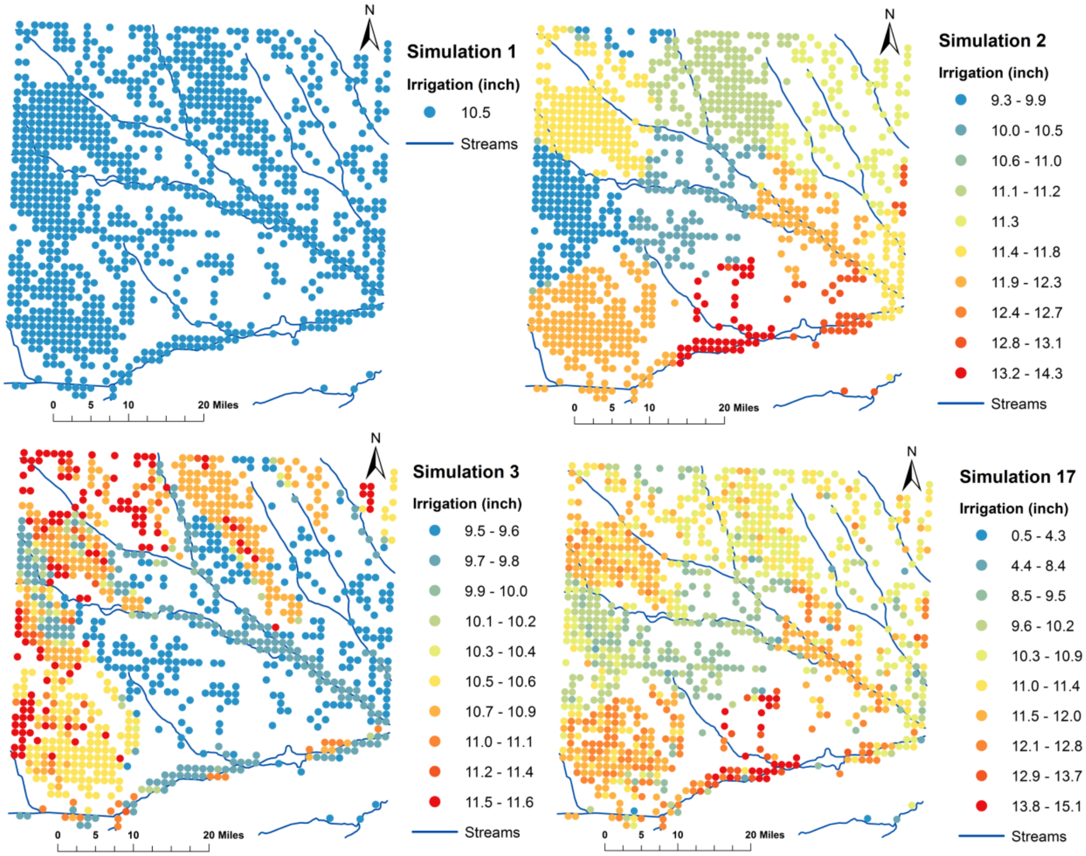

Figure 6: Impacts of behavior heterogeneity on irrigation

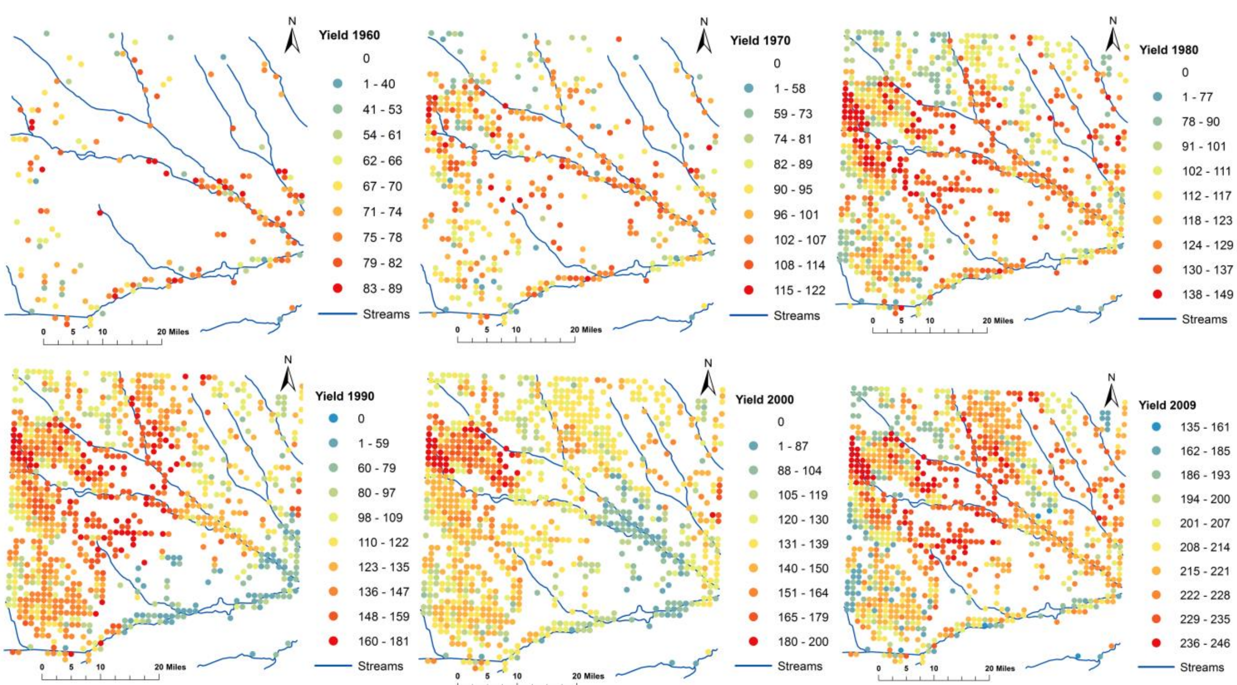

Figure 7: Evolution of corn yield during the 60 years of simulation 16

Overall, individual behavior appears to be a crucial component of the system. When included in the model, it generates complex spatial and temporal patterns. It also leads to better predictions of aggregated system-level variables, in this case corn yield.

3.3.4. Assessing the impacts of system dynamics on individuals

Understanding how individual behavior impacts the system is only one part of the picture. The other important question pertains to the impacts of system dynamics on individuals. When modeling individuals directly, it is possible to keep track of each of them and therefore understand how they are uniquely affected by the system. This provides a lot of insights that can be useful for policy making. As a first example, Figure 8 presents the evolution of farmers' profit due to regulations and decreasing water levels in the aquifer before and after 1980. The black bars show the distribution of profits in the pre-regulation period from 1960 to 1980 for all the farmers active during this period. Most farmers earn between $70 and $100 per acre from selling corn during this period. The grey bars show profit change after 1980 for the farmers in each category. The results here are striking as profit from 1980 to 2009 changes monotonically as a function of profit before 1980. Farmers making only $20 per acre before 1980 saw their profits decrease fourfold after 1980. On the contrary, farmers making $110 per acre before 1980 saw their profits increase by 10% after 1980. Increasing pumping costs and negative impacts of regulations are the main causes for this overall profit decrease. What is interesting here is to see the profit distribution among farmers and how differently they are all impacted by system level phenomena such as regulations and pumping cost.

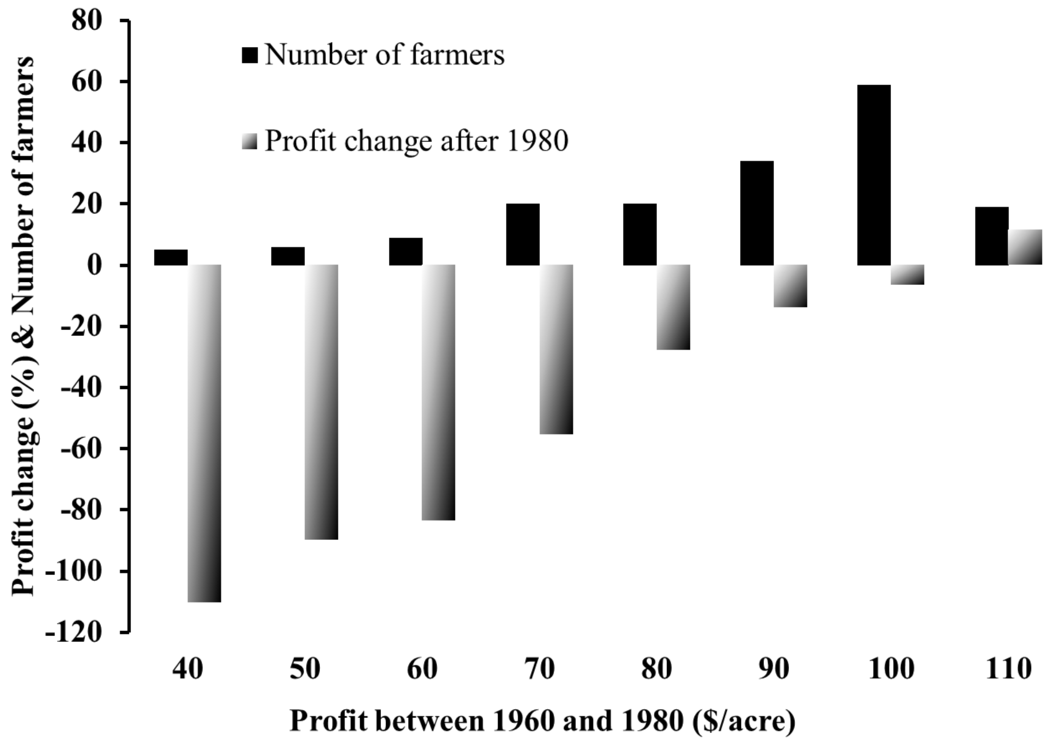

Figure 8: Distribution of average profit between 1960 and 1980 and change of average profit after 1980

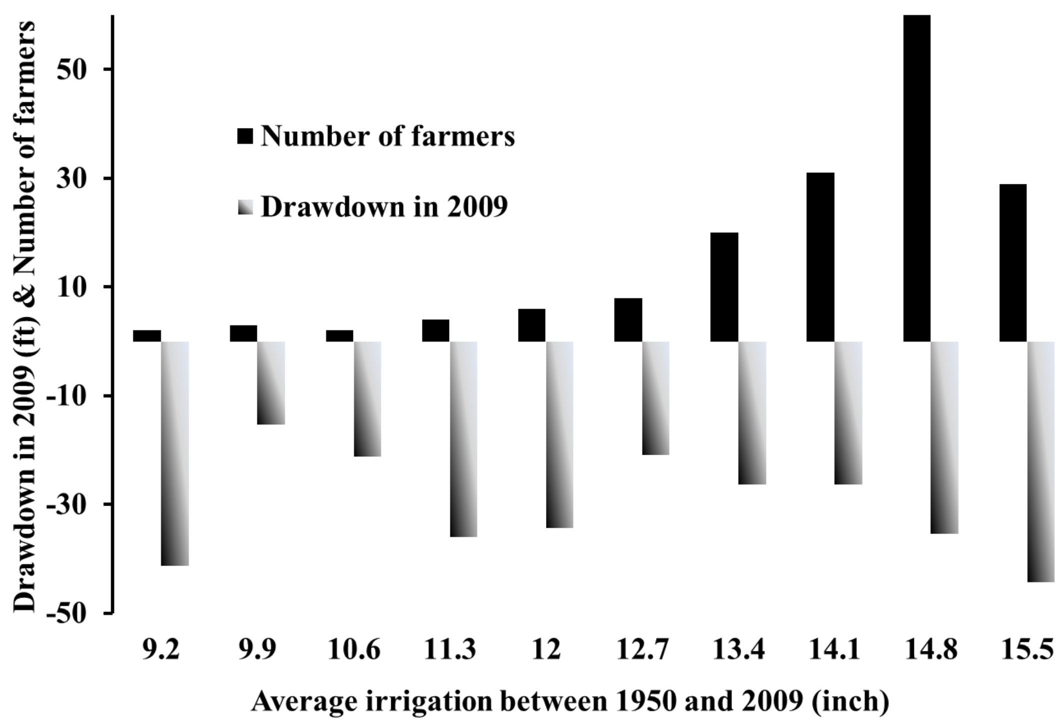

Figure 9: Distribution of average annual irrigation and drawdown in 2009

Figure 9 shows the relationship between average annual irrigation and drawdown in the aquifer. The black bars show the distribution of average annual irrigation for all the farmers active from the 1950s. Most farmers irrigate between 14.1 and 15.5 inches annually on average. The grey bars show the average drawdown in 2009 for the farmers in each irrigation category. Surprisingly, there is no clear pattern and it is not possible to state that farmers that irrigate more cause a higher drawdown in the aquifer or that farmers that irrigate less cause a lower drawdown. The reason for this is that physical characteristics of the aquifer, such as conductivity and thickness of the aquifer, play a crucial role in controlling water level. Depending on these characteristics, similar pumping rates can lead to very different drawdowns. Another reason is that the density of farmers in an area can play a more important role than the pumping rate of individual farmers in causing drawdown. Similar to the conclusion drawn from figure 8, this result has implications from a policy making perspective as it shows that drawdown might not be directly related to pumping intensity. Indeed, Figure 9 shows that farmers with the lowest irrigation depth see almost the highest drawdown in their wells. These farmers are negatively impacted by other farmers' behavior and by the physical properties of the aquifer. It is worth noting that the relation between pumping rate and stream depletion is even more complex than the relation between pumping rate and drawdown.

These results show again the importance of taking individuals into account in CHANS. Not only do individuals impact the system significantly, but they are also uniquely impacted by the system dynamics, a fact that has important implications from a policy making and management perspective.

3.4. Discussion

3.4.1. The role of individuals in systems driven by water demand

Our results show that individuals and their behavior are at the core of the dynamics of CHANS and in particular systems where irrigation is the link between the human and the natural systems. Indeed, section 3.3. showed that accounting for individual's behavioral heterogeneity regarding irrigation leads to the emergence of complex spatial patterns. It was also shown that modeling individual behavior as accurately as possible leads to better prediction of aggregated results at the system level. Instead of continuingly focusing on greater levels of refinement and detail of physical models of natural systems, these two findings support the claim that depicting the distributed, heterogeneous nature of human impacts can also greatly benefit CHANS models. Including individuals and modeling their behavior as accurately as possible allows the understanding of the effects system dynamics on these individuals, as presented in section 3.4. This is particularly relevant to models that are used for policy making, as it is necessary to understand how different individuals are uniquely affected by policies and environmental change. However, questions remain regarding how to represent the full complexity of individual behavior within our models.

The results presented in sections 3.3 and 3.4 illustrate the importance of individuals in CHANS, especially when the natural system is a water or hydrologic system. Accounting for individuals, heterogeneity and behavior is not new in disciplines where the human system is at the center of the system dynamics. The study of individual behavior is particularly important in the field of water demand management. Managing water resources systems is usually incredibly difficult not only because of the variability and uncertainty related to climate and hydrology, but also because of the uncertainty and variability related to water demand. Most water resources systems are dedicated to individuals that need water, whether these individuals are household owners, farmers, fishermen, or users of recreational bodies of water. Understanding these users is therefore a key component of sound management and policy, especially when a resource is scarce and conservation becomes a major concern. Jorgensen et al. (2009), for example, developed an integrated model to better understand household water use behavior. They find that trust is a crucial factor of household water consumption, even though such behavioral characteristic of individuals would be overlooked in most studies. Russell and Fielding (2010) go even further by studying the psychology of water users in order to understand water conservation behavior. They identify five causes of residential water conservation behaviors: attitudes, beliefs, habits or routines, personal capabilities, and contextual factors. These two examples illustrate the importance of understanding individual behavior to study water demand patterns and devise better policies for water conservation.

What is true for residential water management holds for irrigation management. Irrigation varies in space and time and from farmer to farmer and water conservation policies can only be more successful with a better understanding of these irrigation patterns. Sauer et al. (2010) showed that irrigation development and practices have impacts even at the global scale.

3.4.2. More complex behavioral models

While physical attributes of farmers' behavior can be measured and easily incorporated in models, it is more difficult to characterize the psychological, social or personal attributes of farmers' behavior as these attributes are hard to quantify and to incorporate in models. The influence of these attributes should nonetheless be studied as they can have non-negligible impacts on the system. As a first example, Figure 10 illustrates how irrigation varies from year to year and between farmers in simulation 17 where farmers' preferences over crop stress were incorporated in the model. The figure shows a box plot of irrigation and blue dots representing average annual precipitation over the region. This figure shows how water demand for irrigation changes with time, partially because of precipitation variability, but also because of the behavior heterogeneity among farmers. Some years show high irrigation variability between farmers and other years show much lower variability. It is important to note that the number of active farmers in the simulation increases with time which also has impacts on the variability. In 1980 for example, a farmer with very low annual irrigation rates becomes active, keeping the minimum irrigation very low for the rest of the simulation period. Other patterns can be found like the decrease of maximum irrigation due to stricter regulations. Figure 10 highlights the role of individual behavior in creating spatial and temporal patterns of water demand.

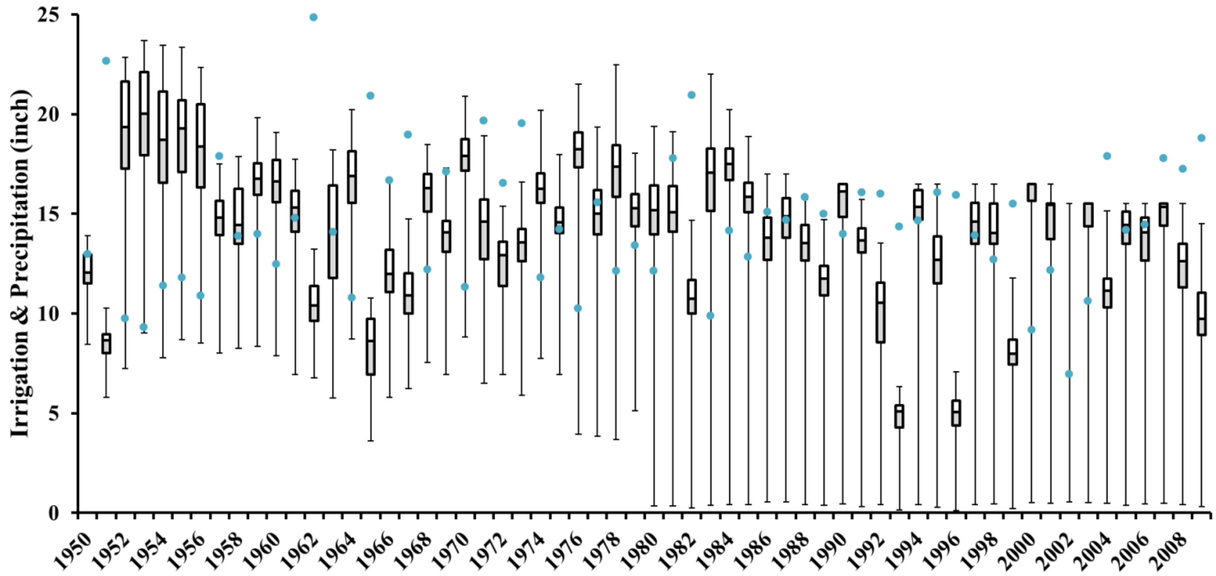

Figure 10: Box plot of annual irrigation for baseline simulation and blue dots representing average annual precipitation in the region

The underlying assumption for simulation 17 was that farmers' irrigation behavior does not only depend on physical characteristics but also on less quantifiable human characteristics. This psychological component of individual behavior was accounted for in a simple way by assuming a normally distributed random variability in individuals' behavior. However, there are numerous ways to model these human or social characteristics of individual behavior. It is possible to model how individuals interact with and influence each other, how they change their behavior with time and how they adapt. An example of a more complex behavioral model for farmers can be found in Ng et al. (2011). The main challenge when making assumptions on how individuals behave and what part of their behavior to model is the inherent difficulty in verifying and validating these assumptions. This challenge should deter researchers from including complex behavior in models if this added complexity does not bring any significant changes in the overall results. But if the impacts of modeling complex behaviors are significant, it might be inappropriate to simply dismiss these behaviors without further investigation.

As an example, the behavior of farmers was changed to adapt with time in a separate simulation. In this new simulation, farmers assess their corn yield compared to the average corn yield in the region every year. They also assess their annual pumping cost compared to the average annual pumping cost in the region. Farmers with the lowest yield then become more sensitive to crop stress and therefore irrigate more the following year. Farmers with the highest pumping cost become less sensitive to crop stress in order to irrigate less the following year. Equation (2) illustrates how the coefficient SC is updated every year as explained above:

$$SC^{n+1} = SC^{n} + \min\left(\frac{CY - 0.75 \times ACY}{ACY}, 0\right) + \max\left(\frac{PC - 1.5 \times APC}{APC}, 0\right) \quad (2)$$

CY is the corn yield in bushels per acre, ACY is the average corn yield over all farmers in bushels per acre, PC is the pumping cost in dollars per acre, APC is the average pumping cost over all farmers in dollars per acre and n is the previous year. SC is constrained to a range of reasonable values: between 0.8 and 1.2. The equation is explained in more details in Appendix A. This framework was designed to reflect how farmers might adapt their practices based on other farmers' practices. Figures 11 and 12 illustrate the impacts of including such adaptation in the model. Figure 11 shows how farmers' profit is changed in the case with adaptation. The figure shows the distribution of profit change averaged over the 60 years. Surprisingly, profit does not necessary increase in the scenario with adaptation as might be expected. This is due to the fact that some farmers reduce their irrigation because of high pumping cost even though the marginal value of increased yield is higher than the marginal value of decrease pumping cost. Likewise, some farmers increase their irrigation because of low yield but their pumping cost might increase more than their profit gain with the increased yield. Profit change appears to be highly variable with some farmers losing close to $180 per acre on average by adapting their behavior while others gaining close to $80 per acre. Figure 12 shows that there is a significant drawdown difference across the region between the two simulations, which implies that the changes in individual behaviors over time can have system-level impacts. Again, heterogeneity is present with spatial patterns of drawdown difference. Four areas seem to particularly benefit from farmers' adaptive behavior. In these regions up to 16 feet of water are saved in the aquifer in the simulation with adaptive behavior. These results show how adding some complexity to individual's behavior can have significant impacts on both individuals and the environmental system. Such impacts should therefore be assessed based on the most accepted assumptions on human behavior. These results also imply that changing farmer's behavior, encouraging better practices and more generally implement policies targeting individuals can be very effective.

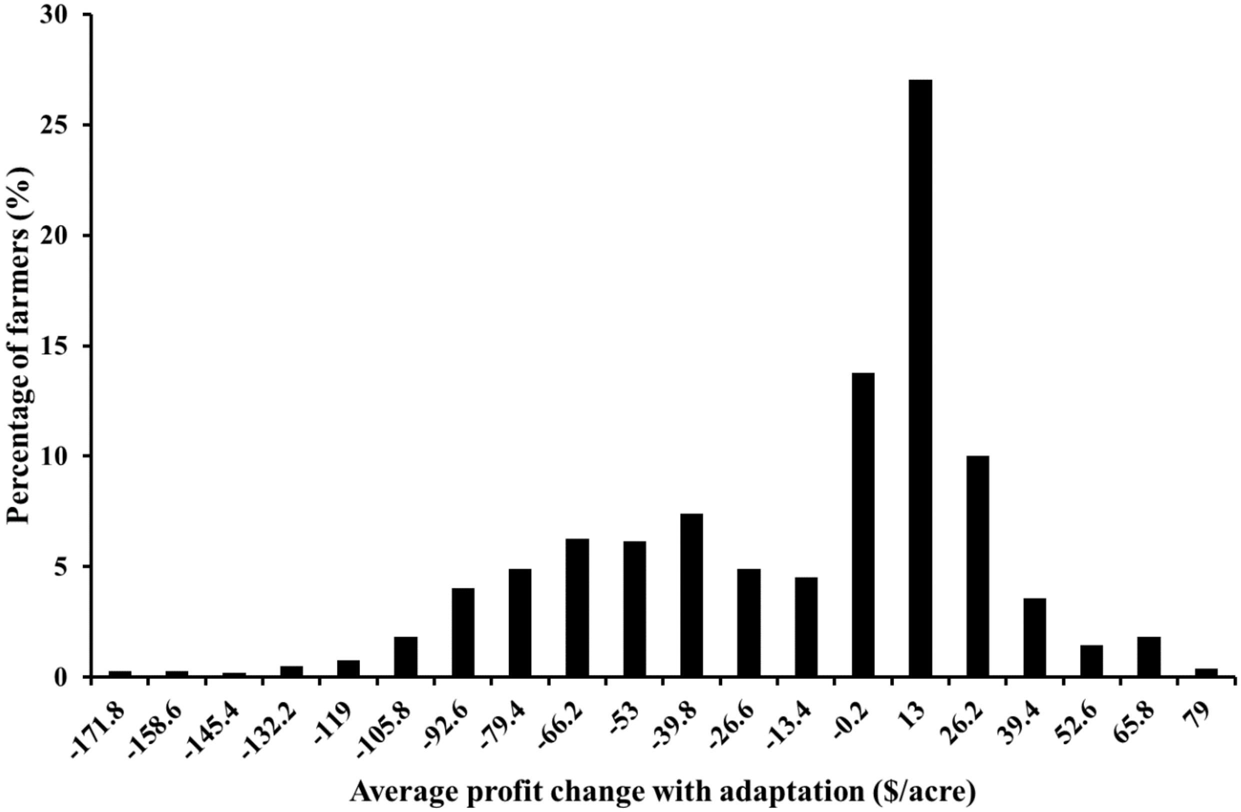

Figure 11: Profit change with behavior adaptation compared to simulation 16

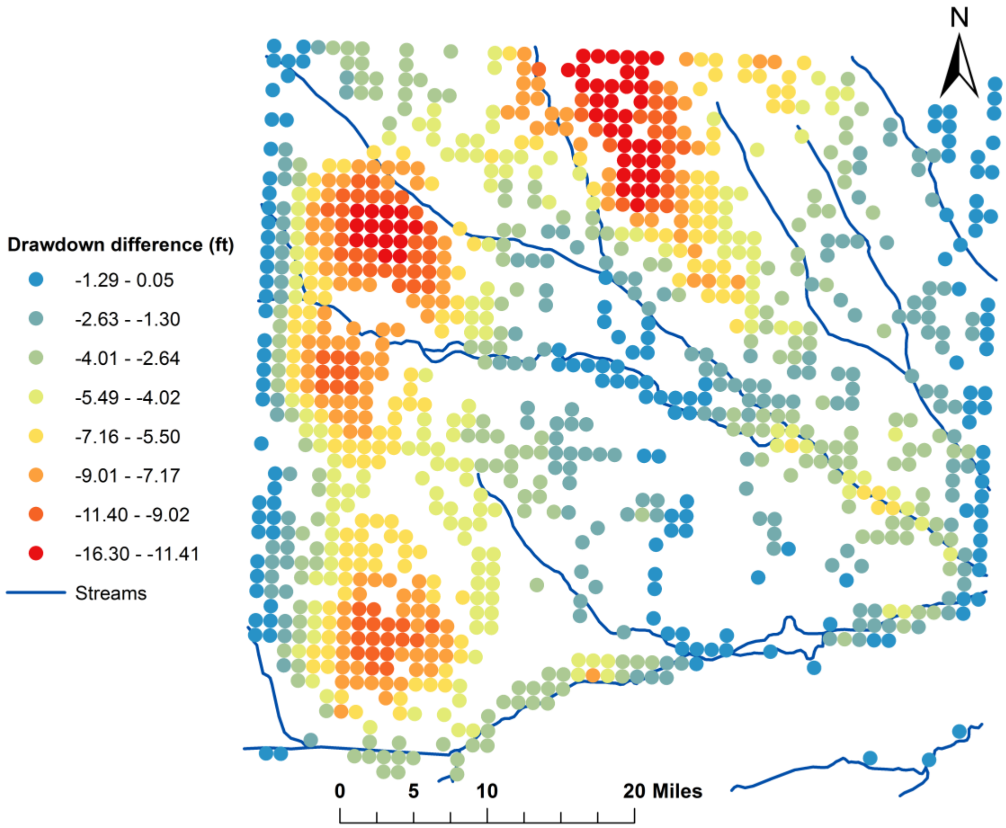

Figure 12: Drawdown difference with behavior adaptation

3.5. Conclusion

The work presented in this paper illustrates the role of individuals in modeling CHANS. We used a model integrating an ABM of farmers' decision-making on irrigation with a groundwater model to study the importance of individuals in an agricultural and hydrologic system. Model results show that accounting for individual heterogeneity has impacts at the system level and leads to the formation of emergent patterns, while also leading to more accurate models. Including individuals in models of CHANS also brings about new understanding of how individuals are impacted by system dynamics, such as new policies or environmental change. Complex individual behavior should be treated as model uncertainty rather than assumed irrelevant or unnecessary. The science of modeling natural systems has made giant steps in the past decades, and the science of modeling human systems should move forward similarly to improve the overall quality of CHANS models. These improved models will in turn reveal some unexpected relationships, feedback loops and emergent patterns, and help devise better policies and management rules.

CHAPTER 4

CONCLUSION

This work attempts to demonstrate why and how to adopt a decentralized perspective when studying coupled human and natural systems. We argue that many, if not most, coupled human and natural systems are decentralized in nature and using decentralized models to study them is therefore one of the most productive approaches. A review of the literature shows that decentralized modeling has already been widely used in different fields to study coupled human and natural systems. Agent-based modeling in particular seems to be well suited to model systems where individuals or other decentralized entities govern the dynamics of the system. We find that these models can be very insightful in situations where individual behavior governs human systems interacting with water systems. Agent-based modeling does have many challenges to overcome but the community seems to agree that it is a very promising tool that has already improved our knowledge of certain systems and interactions with stakeholders. We developed an agent-based model of farmers' decisions on irrigation and coupled it with a groundwater model. This integrated model was designed to capture the interactions between farmers' behavior and their environment in an area located in the Republican River Basin in the High Plains Aquifer region where farmers use groundwater to irrigate their fields to produce cash crops such as corn. The model was used to assess the role of individuals and their behavior in driving the dynamics of this complex system. The model showed that individuals and their behavior play a critical role in shaping spatial and temporal patterns for a range of variables. Moreover, incorporating behavioral heterogeneity of individuals in the model improved the model results. Modeling the human system at the individual level also helps understand how individuals are affected by system dynamics such as new policies and environmental change. The issue is to decide how complex the behavior of individuals should be in these models and we argue that individual behavior should be treated as an additional source of uncertainty rather than a source of unnecessary complexity as assumptions on behavior can have significant impacts on model results.

APPENDIX A

ODD + D PROTOCOL TO DESCRIBE THE MODEL

A.1. Overview

A.1.1. Purpose

The model was developed to simulate the interactions between farmers using groundwater to irrigate their corn fields, and the groundwater and surface water systems. It was designed to capture the co-evolution between the human and the hydrologic systems. In this piece of work, we used the model to assess the role of individuals in coupled human and natural systems. The model was designed for scientific learning and therefore for scientists rather than stakeholders.

A.1.2. Entities, state variables and scales

There are two types of agents in the model: farmers and regulatory agencies. There are 1040 farmer agents and one Natural Resources District (NRD) agent in the case study on the Republican River Basin. There are two other types of entities that are not considered to be active agents: wells and climate stations. Wells are associated with farmers and they simply hold data from the well inventory database. Farmers make decisions on irrigation for each of their well. There are 2166 wells in the region. Climate stations simply provide daily precipitation and potential evapotranspiration data to the farmers. There are 13 climate stations in the region of the case study. Each well is associated with a climate station. Climate stations were allocated to the wells using Thiessen polygons. In other words, we assumed that the climate at each field is similar to the climate at the closest station.

The NRD agent is characterized by five thresholds for the flux of water from the aquifer to the streams and five corresponding irrigations caps. Whenever the flux of water from the aquifer to the streams – a proxy for baseflow – drops under a threshold, a new irrigation regulation is imposed on the farmers in the region. These thresholds were calibrated to ensure that regulations are implemented in the model around the same time as they were implemented historically.

The farmer agents are characterized by several parameters and other attributes. Each farmer has one to several wells. Each well is characterized by a year of activation, a well yield, an irrigated area, a particular soil type (defined by the available water content from the surface to the depth of 30 centimeters and the available water content from the depth of 30 centimeters to the depth of 100 centimeters) and a climate station. Farmers are also characterized by their location (x and y coordinates). Finally, each farmer has a set of variables calculated during each simulation. These variables are daily, monthly and annual values of irrigation and pumping, corn yield at the end of the growing season, profit at the end of the growing season, water table in the aquifer below their farm (updated every month), their personal sensitivity to crop stress (different for different scenarios), and the actual annual irrigated area for each well.

The exogenous drivers of the model are of two types: climatic and economic. Precipitation and potential evapotranspiration provided by the 13 climate stations are exogenous climatic drivers. Corn price, fuel price and costs of the different agricultural inputs (fertilizers, pesticides, labor etc.) are exogenous economic drivers. Note that these economic factors impact farmers' profits but farmers do not consider these variables when making their decisions.

Each farmer is located in space through coordinates and is connected to the groundwater model. For each farmer, a virtual well is created at the center of the farm and the location of the virtual well is used in the groundwater model. The groundwater model is spatially distributed. Many other spatial characteristics are included in the model through the farmers' parameters such as soil type, associated climate stations etc.

The model covers a region of 50 miles by 50 miles. Each farmer is assigned a 1 square-mile farm. Farmers' irrigation decisions are made at the daily scale and the groundwater model is run at the monthly scale. A set of variables such as corn yield and profit are calculated at the annual scale. Farmers decide on the irrigated surface for each well at the annual scale and the NRD agent decides on regulations at the annual scale. All the simulations are performed for the time period from 1950 to 2009.

A.1.3. Process overview and scheduling

Every day, farmers assess if the growing season has started or not – historical growing season dates are used. If the growing season has started and if it is the first day of the growing season, farmers activate their wells based on real well activation dates. Each day, farmers with active wells assess irrigation demand for their corn fields. They decide on daily irrigation supply based on irrigation demand, well yield and annual cap on irrigation. Every month, daily pumping values are aggregated into a monthly value which is used as an input for the groundwater model. Every month, the groundwater model is run. Updated values of water table are provided to all farmers and the updated value of the flux of water from the aquifer to the streams is provided to the NRD agent. At the beginning of each growing season, farmers update the irrigated surface of each of their active well. At the end of each growing season, farmers calculate their annual irrigation value, their corn yield and their annual profit. Each year, the NRD agent assesses the flux of water from the aquifer to the streams and if the value drops under certain thresholds, it updates the irrigation cap imposed on all the farmers.

A.2. Design concepts

A.2.1. Theoretical and empirical

The groundwater model was developed with MODFLOW 2000. MODFLOW uses finite-difference method to solve the three-dimensional groundwater flow equation for a porous medium. It is a fully distributed numerical program designed for high modularity.

The agent-based model is based on several assumptions. We assume that only farmers who irrigate have an impact in the dynamics of the coupled human and natural systems. We also assume that farmers solely grow corn as it is the predominant crop in the area.

Farmers are assumed to follow the water deficit irrigation scheduling method to decide on daily irrigation values. This method is based on a soil water balance approach and was developed by the FAO in its seminal paper on crop evapotranspiration (Allen et al., 1998). Farmers' annual decisions on irrigated area are modeled based on the ratio between actual and potential crop evapotranspiration averaged over three years as described by Rosegrant et al. (2002).

Many irrigation scheduling and water management approaches provided to farmers rely on this method (Rhoads and Yonts, 1991; Lamm et al.; Andales et al., 2011). In practice, farmers can also visually assess soil moisture or use soil moisture sensors to determine soil water deficit and make a decision on irrigation timing and amount (Hanson et al., 2000). Foster et al. (2014) recommend using such intra-annual methodology to model farmers' behavior regarding irrigation as opposed to simulating farmers' behavior at an annual time-step.

All the data sources are shown in Table 1 in the main article.

A.2.2. Individual decision making

The NRD agent decides on regulations based on baseflow values. The farmers decide on irrigation based on soil water deficit, well yield and irrigation regulations. They also decide on irrigated area based on the average over the three previous years of the ratio between potential and actual evapotranspiration. There is no aggregation of the decision-making as it is performed at the individual level.

The NRD agent simply updates regulations based on baseflow values. The farmers do not pursue an explicit objective other than that of limiting crop stress through irrigation and reducing their irrigated land when the evapotranspiration ratio is too negative to the farmer.

Every day, farmer agents have to determine the amount of irrigation to apply on their corn fields. Each farmer owns one to several wells and each well is assumed to be used to irrigate one field through a center-pivot irrigation system. The first step is to determine if the wells should be "activated" or not. Then, for each active well, irrigation demand is calculated as the difference between soil water deficit and the managed allowed deficit:

$$ID = SWD - d_{MAD} \quad (A.1)$$

ID is the irrigation demand, SWD is the soil water deficit and d_{MAD} is the management allowed deficit (all variables are in inches). If SWD is smaller than d_{MAD} irrigation demand is set to 0. SWD is calculated using the soil water balance approach:

$$SWD = SWD_p + ET_c - P - IS \quad (A.2)$$

SWD_p is the soil water deficit from the previous day, ET_c is the corn evapotranspiration, P is the precipitation and IS is the irrigation supply (all variables are in inches). For every field, P and PET, the potential evapotranspiration, are obtained from one of the 13 climate stations used in the area of study, including two interpolated climate stations added to improve the spatial resolution of the climate input. P is the historical precipitation while PET (in inches) is calculated using the Hargreaves equation (Hargreaves, Hargreaves, & Riley, 1985). ET_c is calculated using the equation below:

$$ET_c = k_c \times k_s \times PET \quad (A.3)$$

k_c is the crop coefficient for corn which varies with crop development stages and k_s is a water stress coefficient varying between 0 and 1. Both coefficients are unitless. k_s is estimated based on a simple equation using SWD, the total available water TAW (in inches), and the managed allowed deficit (in %) MAD:

$$k_s = \frac{TAW - SWD}{(1 - MAD) * TAW} \quad (A.4)$$

The total available water is simply the product of the available water capacity of the root zone AWC (inch of water/inch of soil) with the total depth of the root zone D_{rz} (inches). AWC is a characteristic of the soil and the data comes from the STATSGO database. D_{rz} varies during the crop growth season.

$$TAW = AWC \times D_{rz} \quad (A.5)$$

Going back to equation (1), we introduce the sensitivity of farmers to crop stress through a unitless coefficient SF called sensitivity coefficient. This coefficient is used to calculate d_{MAD}.

$$d_{MAD} = \frac{MAD}{100} \times TAW * SC \quad (A.6)$$

A high SC means that the farmer is less sensitive to crop stress and therefore he will tend to irrigate less. In simulations 1 to 16 presented in the paper, SC is equal to 1 for all farmers. In simulation 17, SC is normally distributed with a mean of 1 and a standard deviation of 0.01. In the simulation with behavior adaptation, SC is updated each year with the following equation:

$$SC^{n+1} = SC^{n} + \min\left(\frac{CY - 0.75 \times ACY}{ACY}, 0\right) + \max\left(\frac{PC - 1.5 \times APC}{APC}, 0\right) \quad (A.7)$$

where SC^n is the sensitivity to crop stress coefficient on the previous year n, CY is the corn yield, ACY is the average corn yield over all the farmers, PC is the pumping cost and APC is the average pumping cost over all the farmers. This equation means that SC is decreased when a farmer's corn yield is lower than 75% of the average corn yield over all farmers, and it is increased when a farmer's pumping cost is higher than 150% of the average pumping cost over all farmers.

After daily irrigation demand is calculated, a farmer agent calculates daily irrigation supply for each active well. The first factor to take into consideration is the well yield. It is assumed that a well can only be pumped for 20 hours per day. Knowing the acreage A of each field and the irrigation efficiency IE assumed to be 90% in the model – a typical value for center-pivot, it is then possible to determine if the necessary pumping rate PR (in gallons per minute) is above or below the well yield WY.

$$IS = \begin{cases} ID & if\ PR < WY \\ 0.0442 \times \frac{WY}{A} & if\ PR \geq WY \end{cases} \quad (A.8)$$

$$PR = \frac{ID \times A}{0.0442 \times IE} \quad (A.9)$$

IS is later updated based on annual irrigation AI and the current regulation R followed by the farmer (both in inch).

$$IS = \begin{cases} IS & if\ AI + IS \leq R \\ 0 & otherwise \end{cases} \quad (A.10)$$

Corn yield is calculated as the product of the maximum corn yield CY_{max} and the yield ratio:

$$CY = CY_{max} \times YR \quad (A.11)$$

CY_{max} is calculated with an equation used to calibrate corn yield which accounts for the increase of maximum corn yield with time due to improving agricultural practices:

$$CY_{max} = \begin{cases} 4 \times n + 76.937\ if\ n \leq 38 \\ 200 \times \log\big((n-1) \times 2\big) - 150\ otherwise \end{cases} \quad (A.12)$$

The yield ratio is calculated as the product of the ratio of actual (ET_c) and potential (ET_x) evapotranspiration over six stages of the growing period following Jensen (Jensen, 1968):

$$YR = \prod_{i=1}^{6} \left(1 - k_y \left(\frac{ET_c^i}{ET_x^i}\right)\right) \quad (A.13)$$

Finally, net profit is calculated as profit from selling corn less the different costs for each field:

$$P = \sum_{w \in W} (CP - DHC) \times CY_w \times A_w - A_w \times FC - PC_w \quad (A.14)$$

with W the ensemble of wells owned by a farmer, CP the corn price, DHC the drying and harvesting cost, FC the fixed costs and PC the pumping cost. PC is calculated with the following equation:

$$PC = DC \times PR \times \frac{(WD + 2.308 \times PP)}{3960} \times TO \times P \quad (A.15)$$

DC is the diesel cost, PR the pumping rate, WD the water depth in the well, PP the pumping pressure – assumed to be 60 psi, TO the time of operation – assumed to be 20 hours and P the performance – assumed to be 8.75 hp.hr/gal for a center-pivot pump.

Social norms and cultural values do not play a role in the decision making process and uncertainty is not included in the farmers' decision rules.

A.2.3. Learning

Individual learning is not included in the decision making process.

A.2.4. Individual sensing

The NRD agent is able to sense baseflow to make its decisions on regulations. Farmers are able to sense soil water deficit.

A.2.5. Individual prediction

None of the agents have prediction abilities.

A.2.6. Interactions

Interactions among agents are supposed to be both direct and indirect. The NRD agent directly impacts the farmers through regulations. The farmers indirectly affect each other through their impacts on groundwater.

A.2.7. Collectives

There is no aggregation of individuals in the model and there are no collectives.

A.2.8. Heterogeneity

Farmers are considered heterogeneous. Heterogeneity is included in six parameters: well activation year, well yield, irrigated surface, soil type, climate and sensitivity to crop stress. The decision-making processes are similar for all agents.

A.2.9. Stochasticity

Stochasticity is not included in the model.

A.2.10. Observation

Pumping values are collected at the monthly scale to be used as input for the groundwater model. Average annual irrigation, average corn yield, average profit, average pumping cost, the flux of water from the aquifer to the streams, total irrigated acres, total annual water use and total corn production are saved in an Excel file each year. Water-table, annual irrigation, annual corn yield, irrigated acres, profit and annual pumping cost are saved for each farmer in an Excel file every year.

Model results show the emergence of spatial and temporal patterns of irrigation, profit and corn yield. They also show spatial and temporal patterns of groundwater depletion across the region and of streamflow depletion.

A.3. Details

A.3.1. Implementation details

The model was implemented using Repast Simphony. Repast Simphony is a library incorporated to Eclipse IDE to develop agent-based models in the object-oriented Java language. The groundwater model was developed with Modflow 2000. The Java code creates text files using data from the ABM to input to the groundwater model and reads the text files outputted by the groundwater model to input data in the ABM.

The model is accessible upon request. Repast Simphony 2.1 and Eclipse IDE are required to run the model.

A.3.2. Initialization and input data

When the model is initialized, all the farmers are created. A table containing well data is read and wells are assigned to farmers. Climate stations are created and climate data for the entire simulation is read from a table for each of them. Initial values for SC are assigned depending on the type of simulation.

A.3.3. Submodels

There are no submodels in this model.

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