



RESEARCH ARTICLE

10.1002/2017WR021420

Special Section:

Socio-hydrology: Spatial and Temporal Dynamics of Coupled Human-Water Systems

Key Points:

- We present a socio-hydrological model that captures a farmer's crop choice and water allocation given his perception of water availability
- We show how "satisficing" crop patterns can emerge also when each farmer is assumed to follow simple decision rules guided by his perception
- In line with bounded rationality theory, the model offers an alternative to normative models and can support climate adaptation research

Supporting Information:

Supporting Information S1

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Citation:

Kuil, L., Evans, T., McCord, P. F., Salinas, J.L., & Blöschl, G. (2018). Exploring the influence of smallholders' perceptions regarding water availability on crop choice and water allocation through socio-hydrological modeling. *Water Resources Research*, *54*, 2580–2604. https://doi.org/10.1002/ 2017WR021420

Received 29 JUN 2017 Accepted 7 MAR 2018 Accepted article online 12 MAR 2018 Published online 2 APR 2018

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Exploring the Influence of Smallholders' Perceptions Regarding Water Availability on Crop Choice and Water Allocation Through Socio-Hydrological Modeling

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Abstract While it is known that farmers adopt different decision-making behaviors to cope with stresses, it remains challenging to capture this diversity in formal model frameworks that are used to advance theory and inform policy. Guided by cognitive theory and the theory of bounded rationality, this research develops a novel, socio-hydrological model framework that can explore how a farmer's perception of water availability impacts crop choice and water allocation. The model is informed by a rich empirical data set at the household level collected during 2013 in Kenya's Upper Ewaso Ng'iro basin that shows that the crop type cultivated is correlated with water availability. The model is able to simulate this pattern and shows that near-optimal or "satisficing" crop patterns can emerge also when farmers were to make use of simple decision rules and have diverse perceptions on water availability. By focusing on farmer decision making it also captures the rebound effect, i.e., as additional water becomes available through the improvement of crop efficiencies it will be reallocated on the farm instead of flowing downstream, as a farmer will adjust his (her) water allocation and crop pattern to the new water conditions. This study is valuable as it is consistent with the theory of bounded rationality, and thus offers an alternative, descriptive model in addition to normative models. The framework can be used to understand the potential impact of climate change on the socio-hydrological system, to simulate and test various assumptions regarding farmer behavior and to evaluate policy interventions.

1. Introduction

A typical smallholder farm can be described as a household in which mainly family labor is used and for which the farm provides a principal source of income (*Cornish*, 1998 in Morton, 2007). Of the more than 570 million farms worldwide, 84% are smaller than 2 ha. In low-income and lower-middle-income countries, smallholders can operate up to 40% of the land (Lowder et al., 2016) and play a significant role in providing food security (Salami et al., 2010). Multiple stressors including resource uncertainty and population pressure threaten the viability of these small-scale enterprises (Van Vliet et al., 2015). Such is the case for Mount Kenya's Upper Ewaso Ng'iro Basin, where population has grown by 5–6% per year in recent decades, mostly as a result of immigration of people from nearby areas in search of available farmland (Gichuki, 2002; Ngigi et al., 2007). With the recent wave of immigration, water extraction points have more than doubled and concerns over water scarcity have increased.

In order to support farmers in adopting more sustainable practices, understanding of their perceptions and decision-making behavior is important (Feola & Binder, 2010; Öhlmér et al., 1998). Previous research has focused on elucidating the factors that influence farmers' decisions to adopt new technologies. Factors include age, education, wealth, personality, access to extension, and perceptions of weather and risk (Bryan et al., 2009; Jain et al., 2015; Rao et al., 2011). The decision-making process has been conceptualized as steps, e.g., defining the problem, analyzing options, making the decision and evaluating its outcome, or in descriptive terms (Feola & Binder, 2010; Öhlmér et al., 1998; Risbey et al., 1999). For example, Öhlmér et al. (1998) describe the decision-making process of Swedish farmers as a nonlinear, evolving process. Distinguishing between analytical and intuitive farmers, they found that analytical farmers formulated

quantitative goals and took into account calculations of the consequences of various options in their decision making. Intuitive farmers, on the other hand, had not formulated quantitative, but intuitive goals with the aid of experience, reference points, and other information about possible performance. Objectives were often in the form of a direction, such as "an increase in production".

The description of farmer decision making by Ohlmér et al. (1998) is illustrative for decision-making theories. The theory of expected utility, for example, makes the assumption that humans are capable of making rational decisions and able to choose the optimal outcome considering all possible combinations based on perfect information (Koehler & Harvey, 2008). However, humans often do not behave optimally (Koehler & Harvey, 2008; Van den Bergh et al., 2000; World Bank, 2015). The complex calculations that computer models perform in order to obtain the best solution are not the calculations the human mind makes. Neither is it generally trained to handle probabilities very well (Elliott, 2003). Rather, each individual has developed (and continues to develop) a unique frame of reference or lens in order to easily focus, categorize and interpret information, based on his (her) own experiences (Elliott, 2003). Each individual perceives the world differently. While professionals might be trained to interpret information analytically, the lay public relies more heavily on reflective learning and personal experiences. Experience is encoded in the brain as memory and shapes present and future functioning (Beratan, 2007). Any decision process begins with a human brain responding to some sensory input. The brain seems to strategically filter incoming key information by a predictive model to cope with the vast quantity of information (Beratan, 2007). This is one likely reason why cognitive biases or deviations from "good, objective judgment" might occur (Merz et al., 2015). Alternative decision-making theories include the theory of planned behavior (Ajzen, 1991), prospect theory (Kahneman & Tversky, 1979) and the theory of bounded rationality (Simon, 1955). The latter emphasizes that rational behavior will be bounded or limited given practical considerations such as time and information constraints. If maximizing objective utility is out of reach, behavior is aimed at satisficing oneself, and a variety of decision heuristics or simplification mechanisms are used to choose between alternative options.

Ideally the diversity of decision-making strategies is reflected in formal model frameworks developed to study the interactions between humans and their environment (Pahl-Wostl, 2002; Schlüter et al., 2017). Yet, often models include behavioral assumptions based on expected utility (Schlüter et al., 2017). While these provide a picture of how humans ought to behave or how resources ought to be optimally distributed, they only present one side of the spectrum, i.e., the most positive or optimal outcome. It is equally important to gain insight in the status quo, i.e., how do people actually behave. Increased understanding regarding the latter can aid in policy development with regards to deciding how and when to intervene and can help increase the uptake of recommendations suggested by decision support systems based on optimality assumptions (Cox, 1996). The integration of perceptions and decision making into formal models remains challenging, however, due to a number of issues including the difficulty in capturing the variability in factors affecting decision making (such as how weather events alter crop and harvesting decisions, Bradshaw et al., 2004; Edwards-Jones, 2006).

The aim of this paper therefore is to construct a descriptive, coupled modeling framework that captures the interactions between farmers and their environment in the context of crop choice and water allocation. We take a socio-hydrological approach aimed at understanding the evolution of coupled human-natural systems (Folke, 2006; Pahl-Wostl, 2002; Schlüter et al., 2017; Sivapalan et al., 2012). Also, as we are interested in the potential mechanisms behind observed behavior, we adopt a stylized approach. Several socio-hydrological studies have already incorporated insights from sociology and psychology into quantitative, dynamic models leading to an increased understanding of system functioning (Di Baldassarre et al., 2013, 2017; Elshafei et al., 2014; Garcia et al., 2016; Kuil et al., 2016; Le et al., 2012; Tsai et al., 2015; Viglione et al., 2014; Yu et al., 2017).

Guided by the steps put forward in Sivapalan and Blöschl (2015), presented to help frame and model human-water interactions in general, we first develop a descriptive conceptual model of how farmers allocate water and select the crops on the basis of how they perceive water availability. We subsequently translate the conceptual model into a stylized mathematical model. We parameterize the model to simulate the water allocation and crop planting decision of smallholders in the Upper Ewaso Ngi'ro Basin in Kenya. This is possible through the availability of a rich, cross-sectional data set collected during 2013 that includes information on crop choices and water management strategies at the household level. Using the calibrated model, we explore how different perceptions of water availability could impact water allocation and crop

choice and how a farmer, given his (her) perceptions and management strategy, responds to changes in eco-hydrological characteristics.

Through exploring interactions in a stylized model, we envision to gain insights regarding the underlying socio-hydrological dynamics present in a complex agricultural system. The model provides a socio-hydrological base line, to which actual behavior subject to multiple drivers can be compared. By making perceptions regarding water availability a central component of the model, the model framework not only acknowledges insights from cognitive theory, but also provides a framework to simulate and test various assumptions regarding farmers' behavior, for example, in the light of current climate adaptation research (Bradshaw et al., 2004; Bryan et al., 2009; Smit et al., 2000). A better understanding of the role of perceptions of farmers can help focus policy development aimed at improving farm management.

2. Conceptual Model

The circumstances within which smallholder farming systems occur are diverse due to various biophysical and socio-economic circumstances (Tittonell et al., 2010). Land use patterns and agricultural management practices are influenced by agroecology, market and local cultures, as well as household specific characteristics, such as resource endowment, production orientation and objectives, ethnicity, education, past experience and management skills, and attitudes toward risk. Farmers are likely to use various decision mechanisms depending on the problem at hand and depending on their personality (Öhlmér et al., 1998). The model framework presented here is therefore not the only representation possible, but one possibility of many. It is based on cognitive theory, by focusing on perceptions and experiences as a basis for actions, and on bounded rationality theory, by explicitly incorporating decision making on the basis of imperfect information and strategies aimed at simplifying the problem.

In order to start our conceptualization, we imagine that a smallholder has just obtained a plot of land. In addition, he was able to secure access to irrigation water. Depending on the farmer's history, it could be that he has no previous experience with regard to agriculture (he used to be a pastoralist and was forced to take up agriculture), he has experience with agricultural farming (his parents were also farmers) or he has a considerable amount of knowledge (he just completed an agricultural degree). Given the many crop types and varieties, which crops is the farmer going to cultivate? How many acres does he assign to each crop? And how does he allocate his resources?

In absence of perfect information regarding soil, weather patterns, irrigation reliability or crop characteristics and considering the limited time he has until the growing season starts, he may look for ways to eliminate options and to simplify the problem, i.e., general strategies often adopted to tackle a multiattribute choice problem (Berretty et al., 1999; Koehler & Harvey, 2008). He might take into account information from his family or from neighbors in absence of any experience of his own, thereby eliminating a range of crops. Instead of relying on complex, detailed, quantitative information, he might classify (or rank) crops as being low or high priced, low or high input demanding or as staple food versus potential money making crop. An inexperienced farmer may subconsciously adopt relatively risk averse behavior. In the first year, he assigns a large share of his land to a relatively low cost, low demanding staple food (crop 1), and a small amount of land to more risky, resource demanding crops (crop 2). This is shown in Figure 1 (Year 1). During the growing season, the crop pattern is fixed and the farmer allocates water, fertilizer and manages weed and pests in line with his perceptions and to the extent he can afford this (Rao et al., 2011). All his efforts will have an impact on final yields. After the growing season the farmer evaluates (Dury et al., 2013; Ingram et al., 2002). When he finds himself in the position of having had sufficient resources to satisfy the more risky (drought intolerant) resource demanding crop, as well as having achieved reasonable yields from the relative drought-tolerant staple crops, he might decide to expand the area of the more risky, market crop (and reduce the area of the staple crop). Stepwise, he is able to increase the fraction of crop 2 year after year, until, for example, year 6. Unexpectedly, rainfall and irrigation water turn out to be below normal and the farmer finds himself short of water. Yields are suddenly set back after a steady rise for the past couple of seasons. Providing that the farmer has sufficient means to stay in the farming business, the farmer might revise his strategy for the next season. Based on his experience or memory, he now decides to decrease the share of crop 2 and plants a larger share of the less demanding staple crop (crop 1) (Year 7 in Figure 1). This





Figure 1. Illustration of the stepwise adjustment of the crop fraction on the basis of farmer's updated memory of the crops' water deficits such that the cropping pattern will ultimately reflect the prevailing socio-hydrological conditions.

stepwise, learning by doing, allows the farmer to reach a crop pattern that is feasible given the prevailing climatic conditions.

While we have constructed this narrative for one farmer, one can imagine similar narratives for other farmers. For each farmer, starting conditions are likely to vary due to the differences in information, resources,



Figure 2. Schematic of socio-hydrological interactions in a smallholder community. The state variables, i.e., soil moisture storage $(S_{1,2})$, memory $(M_{1,2})$, and the drought-intolerant crop fraction (C_2) of the ordinary differential equation (ode) system are in black. The exogenous fluxes, i.e., precipitation (*P*) and irrigation (*I*), are in red. Irrigation water allocation, i.e., I_1 and I_2 (orange), varies based on M_1 , M_2 , C_2 , and *I*. Crop yields, i.e., Y_1 and Y_2 , are in green. Plus and minus signs indicate whether one variable increases or decreases another variable, respectively. Parallels can be drawn with the socio-hydrological system conceptualization of Kuil et al. (2016). Here however, we go beyond irrigation water supply and include crop decision making as an additional adaptive response.

and personal characteristics as described earlier. Similarly, perceptions of resource (water) availability will be constructed differently, as well as the rate at which each farmer will react on the basis of his perceptions. While the actual crops will be chosen on the basis of various factors in addition to water availability, the farmer needs to adopt an optimizing or a satisficing strategy regarding water needs independent of the chosen crop mix.

Since we are interested in the interaction between the hydrology (water availability) and the social system (farmer behavior), we focus on the conceptualization of the water management aspects of the problem. In line with socio-hydrological thinking, i.e., humans and water systems are coupled such that human-water systems coevolve, our aim is to bring about potential two-way causal relationships between actions or variables. To our knowledge, no studies exist that explicitly deal with water allocation and crop decision making in such a descriptive, coupled way. We also realize that we are dealing with a highly complex system, and the model constructed here may be considered as hypotheses of the relationships that exist between different variables (Troy et al., 2015). We focus on two common management strategies, the choice of the crop and the irrigation water supplied, although various strategies exist to improve crop management in water-limited environments (Debaeke & Aboudrare, 2004).

The crop decision-making approach is formalized in the flow diagram of Figure 2. The process is conceptualized using two representative crops: crop 1—the drought tolerant, low demanding crop, and crop 2—the riskier, drought-intolerant crop. The variables that are used to represent the socio-hydrological system are precipitation (*P*), irrigation water (l_1 , l_2), soil moisture (S_1 , S_2), crop fraction (C_1 , C_2), and memory (M_1 , M_2). The subscripts 1 and 2 used in each of the variables refer to crop 1 and crop 2,

respectively. C_1 thus represents the fraction land the farmer allocates to crop 1, while C_2 represent the fraction of land the farmer allocates to crop 2 is denoted by C_2 . Assuming a unit area, C_1 is calculated as $1 - C_2$, and is therefore not shown in the figure. As we stated in section 1, any decision process begins with a human brain responding to some sensory input (Beratan, 2007). In order for the farmer to respond to the hydrological system, he thus needs to be aware of the status of the hydrological system (e.g., How much water is available? How dry is my soil?). We therefore conceptualize that the farmer builds up memories, M_1 and M_2 , which are measures of the farmer's perception of each crop's water deficit at a given time. While the farmer's perception of this deficit can be constructed on the basis of multiple information sources, such as actual precipitation, the weather forecast, or information from neighbors, we assume, for simplicity, that he bases his memory only on his perception of the soil moisture available. The actual soil moisture available to crop 1 and crop 2 are denoted by S_1 and S_2 , respectively. Crops receive water via precipitation, P, and Irrigation, I. The difference between the two fluxes is that a farmer is able to decide how to allocate the available irrigation water, hence I_1 and I_2 , while this is not the case for precipitation. The yields produced by each crop are denoted by Y_1 and Y_2 .

Now, to read the flow diagram assume that both crops received equal amounts of rain but, over time, the soil of crop 2 becomes drier than the soil of crop 1, since crop 2 is the more water demanding crop. Thus soil moisture $S_2 < S_1$. A farmer registers this, possibly with errors, and the farmer's memory of crop 2's water deficit $M_2 > M_1$. The farmer can respond in two ways, he can either influence irrigation water (arrows from M_1 and M_2 to I_2) or he can influence the crop fraction (arrows from M_1 to M_2 to C_2). Assume we are in the middle of the growing season and it is impossible for the farmers to influence crop fraction C₂. The only tool the farmer has is to allocate irrigation water. In absence of perfect information, we assume he adopts a simple rule and decides to always allocate the available water supply to the crop that needs water the most (according to his memory). With increasing memory M_2 or with decreasing M_1 , the farmer will increase irrigation water to crop 2, i.e., I_2 (indicated by the + and - sign, respectively). An increase in irrigation water I_2 means an increase in soil moisture S_2 (+ sign) which means a decrease in the farmer's memory M_2 (- sign). At the same time, an increase in I_2 implies a decrease in I_1 (- sign) as a limited amount of irrigation water is available. This results, under continued evapotranspiration, in a decrease in S_1 (+ sign) and an increase in M_1 (- sign). The feedback continues until the balance between S_2 and S_1 and consequently M_2 and M_1 is restored. Alternatively, it is possible that the feedback cannot be restored. This could happen when the farmer has no or insufficient irrigation water available to satisfy the demand of the crops. If this is the case, the farmer is able to respond outside of the growing season by adjusting the crop fraction. Now, a higher memory for crop 2, i.e., M_2 , relative to M_1 , motivates the farmer to decrease the share of crop 2 and crop fraction C₂ goes down. Consequently, the overall water demand of the farmer's crop area is reduced and the balance between M_2 and M_1 is restored: when the same amount of irrigation water is applied over less area, S_2 will increase, M_2 will decrease and so on.

3. Functional Relationships

This section presents the stylized model that formalizes the dynamics described in section 2. A summary of the model equations and parameters can be found in supporting information Table S1. We assume that the dynamic evolution of the state variables, i.e., soil moisture storage $(S_{1,2})$, memory $(M_{1,2})$ and the drought-intolerant crop fraction (C_2) can be captured by nonlinear differential equations in a continuous state space. The use of differential equations is motivated by the flexibility of the approach, which allows one to gain insight into complex systems, characterized by two-way interactions, even when data availability is limited (Brown, 2007). We conceptualize the processes for a representative unit area.

3.1. Hydrology (S)

The hydrology is modeled as two water balance equations per unit area for the drought-tolerant crop (C_1) and the drought-intolerant crop (C_2). $S_{1,2}$ [L] represents the soil moisture per unit area. For brevity, double indices (e.g., $S_{1,2}$) refer to both crop types separately:

$$\frac{dS_{1,2}}{dt} = P + I_{1,2} - T_{1,2} - E_{1,2} - Q_{1,2}$$
(1a)

where *P* is precipitation, $I_{1,2}$ irrigation water, $T_{1,2}$ transpiration, $E_{1,2}$ evaporation, and $Q_{1,2}$ runoff. Small differences arise in the formulation of the processes to allow for different crop characteristics and irrigation water allocations, so we specified the process equations for S_1 and S_2 separately.



For S_1 :

$$I_1 = D \frac{1}{C_1} (I - I_2)$$
 (1b)

$$T_1 = D\alpha_{H1} \frac{\mathsf{S}_1}{\varphi_H} \tag{1c}$$

$$E_{1} = (1-D)\beta_{H} \max\left[\frac{S_{1} - (\varphi_{H} - \delta_{H})}{\delta_{H}}, 0\right]$$
(1d)

$$Q_1 = \frac{(P+I_1)}{1+e^{\varepsilon_H\left(\zeta_H - \frac{\varsigma_1}{\varphi_H}\right)}}$$
(1e)

$$I_2 = D \frac{1}{C_2} \frac{I}{1 + e^{\kappa_H ((\beta_C M_1 + \gamma_C) - M_2)}}$$
(1f)

$$T_2 = D\alpha_{H2} \frac{S_2}{\eta_H \varphi_H} \tag{1g}$$

$$E_2 = (1-D)\beta_H \max\left[\frac{S_2 - (\eta_H \varphi_H - \delta_H)}{\delta_H}, 0\right]$$
(1h)

$$Q_2 = \frac{(P+I_2)}{1+e^{\varepsilon_H \left(\zeta_H - \frac{\varsigma_2}{\eta_H \varphi_H}\right)}}$$
(1i)

It is assumed that the soil moisture available to the crop is limited by a maximum. This maximum is the difference between the amount of water that a well-drained soil should hold against gravitational forces, i.e., field capacity, and the amount that is inaccessible for the crop, i.e., wilting point (Allen et al., 1998). For crop 1, maximum water content is represented by parameter φ_H [*L*] (equations (1c)–(1e)). For crop 2, maximum water content is represented by η_H [–] φ_H [*L*], where η_H [–] is a scaling parameter \leq 1 (equations (1g)–(1i)). The smaller η_H , the less water crop 2 has access to. *D* [–] represents a dummy variable to model the growing season, i.e., 0 represents the off-season and 1 the rainy, crop season.

Water availability consists of a precipitation flux, P [L T^{-1}], and an irrigation water flux I [L T^{-1}] per unit area. Both are exogenous to the model. According to our conceptualization, the farmer divides the irrigation water among the two crops (equations (1b) and (1f)) based on the farmer's management strategy, conceptualized by β_{C} [-] and γ_{C} [-], and based on the farmer's memory of water deficit for both crops, i.e., M_1 and M_2 . Hereby it is assumed that the farmer first allocates water to C_2 to fulfill the water needs of crop 2 and only when $M_2 < \beta_C M_1 + \gamma_C$ (equation (1f)), irrigation water to crop 2 goes to zero and water is allocated to C_1 (crop 1). Here β_C [-] and γ_C [-] determine when and how much water is allocated to each crop. For example, a management rule could be to irrigate the crops such that the perceived water deficit of crop 1 equals the perceived water deficit of crop 2. In the model this could be achieved by setting $\beta_{c} = 1$, and $\gamma_{c} = 0$ and only when $M_{2} = M_{1}$, water is allocated to crop 1. Alternatively, the farmer could have a preference for one of the crops and his management strategy would be to always allocate a higher share of irrigation water to this crop to minimize the losses for this crop. This can be achieved by setting $\beta_C \neq 1$ and $\gamma_C \neq 0$, so that either M_2 is always larger than M_1 (if crop 1 is preferred) or M_1 is always larger than M_2 (if crop 2 is preferred). κ_H [-] determines the speed at which the farmer switches from allocating water to crop 2 to crop 1, and vice versa. Division by C_1 (=1 – C_2), respectively, C_2 , is needed to obtain irrigation water depths.

Crop transpiration, $T_{1,2}$, is a function of a maximum transpiration rate, $\alpha_{H1,2}$ [L T^{-1}], and the extent of water stress experienced by the crops (Allen et al., 1998). Water stress is experienced when actual soil water is less than maximum water content, i.e., $S_1 < \varphi_H$ for crop 1 (equation (1c)) and $S_2 < \eta_H \varphi_H$ for crop 2 (equation (1g)). For simplicity, a linear relationship is assumed between transpiration and soil moisture in case of water shortage (see Schaake et al., 1996, for a similar representation). Outside of the crop season (D = 0), it is assumed that fields have minimal crop coverage and thus evaporation, $E_{1,2}$, becomes the dominant process

For S_2 :





(equations (1d) and (1h)). It is a function of a maximum evaporation rate $\beta_H [L T^{-1}]$ and the amount of water available in the soil within the surface soil layer $\delta_H [L]$ that is subject to drying by way of evaporation (Allen et al., 1998). Again, a linear relationship is assumed. Both S_1 and S_2 are scaled by subtracting the soil depth that is not subject to evaporation, so that the ratio that is calculated remains between 0 and 1, where evaporation is at a maximum when soil moisture is at a maximum, and zero when soil moisture in the surface layer is depleted.

Runoff is governed by a logistic function in order to ensure that, when soil moisture $S_{1,2}$ reaches the maximum water content, φ_H or $\eta_H \varphi_{H}$, respectively, any additional precipitation will generate runoff (see Kuil et al., 2016, for an illustration of this concept). The general behavior is that proportionally more runoff will occur when soil moisture $S_{1,2}$ reaches field capacity, and the soil becomes saturated. The function of the dimensionless parameters ε_H and ζ_H is similar to the runoff coefficient.

3.2. Memory (M)

Based on the premises that everyone is observing information through his own frame of reference (Beratan, 2007; Elliott, 2003), every farmer is presumed to have unique perceptions regarding water availability based on his experience. While an individual or farmer can hold these perceptions at different scales i.e., at field scale, community scale or basin scale, we limit our definition for the purpose of this study to field scale. In our conceptualization, memory, e.g., M_1 [-] or M_2 [-], captures the farmer's perceptions regarding the water deficit for each crop. A higher average water deficit is represented by an increased memory. The process is governed by the following equations:

$$\frac{dM_1}{dt} = D \frac{\varphi_H - S_1}{\varphi_H} \alpha_{M1} - \beta_{M1} M_1$$
(2a)

$$\frac{dM_2}{dt} = D \frac{\eta_H \varphi_H - S_2}{\eta_H \varphi_H} \alpha_{M2} - \beta_{M2} M_2$$
(2b)

As becomes apparent from the equations, memory is based on the farmer's perception of each crop's normalized soil moisture deficit, calculated as field capacity minus the actual soil moisture divided by field capacity. $\alpha_{M1,2}$ [T^{-1}] determines the rate at which environmental signals are converted to memory ("encoded" in the psychological literature, Wolf, 2009). The memory encoding rate may vary between individual farmers. For example, one farmer may recognize that the soil is dry, mentally process this situation, and place high importance on it, effectively committing this strongly to memory. Another farmer may recognize that the soil is dry, but places less importance on it (perhaps because at the time he is concerned by other more pressing issues such as pests, employment off the farm, financial concerns or family priorities) and therefore does not commit it strongly to his memory. Additionally, each farmer's memory encoding rate may vary between crops. For example, if the soils of crop 1 and crop 2 become dry, a farmer may process this situation differently, and my place stronger emphasis on the dryness of crop 2 (the higher value crop). He effectively commits the soil moisture deficit of crop 2 more strongly to his memory than that of crop 1. Also, a higher priority on crop 2 may exist even for farmers with a generally low encoding rate (e.g., although they generally place low importance on soil moisture deficit, they commit the dryness of crop 2 more strongly to memory than the dryness of crop 1).

 $\beta_{M1,2}$ [T^{-1}] determines how much of the information committed to memory is stored and available at any given time for retrieval. The loss of memory of an event or situation assumes exponential decay which is in line with the findings of the experimental psychologist Ebbinghaus (1913) and is similar to earlier representations of memory in the socio-hydrological literature (Di Baldassarre et al., 2013; Kuil et al., 2016; Viglione et al., 2014; Yu et al., 2017).

In this model, soil moisture deficits are encoded as memory only during the growing season (D = 1), while loss of memory is a continuous process throughout the year. Ingram et al. (2002) found that water deficit is one of three parameters farmers in Burkino Faso like to be part of their forecast, the others being "the timing of the onset and end of the rainy season" and "the total amount of rainfall."

3.3. Crop Fraction (C)

Crop fraction (C_2) represents the fraction of the unit area that is devoted to crop 2, the riskier, droughtintolerant crop. C_1 is calculated as $1 - C_2$. The equation governing crop decision making is:



$$\frac{dC_2}{dt} = (1 - D)(\alpha_C((\beta_C M_1 + \gamma_C) - M_2)C_2(1 - C_2))$$
(3)

Here $\alpha_C [T^{-1}]$ determines the rate at which a farmer changes crop type as a consequence of changes in memory. $\beta_C [-]$ and $\gamma_C [-]$ represent, similar to their use in equation (1f), management strategy parameters. However, now the parameters influence when and how much the farmer will expand his crop area, C_2 . Assuming the farmer has an equal preference for both crops and M_2 is still larger than $\beta_C M_1 + \gamma_C$ after the growing season, the farmer realizes he did not have sufficient water during the growing season to satisfy the water demands of both crops and will respond by reducing crop area C_2 . Alternatively, if $M_2 < \beta_C M_1 + \gamma_C$, the farmer will expand C_2 . Crop decisions are only made during the off-season (hence 1 - D) and can change until the last moment, reflecting field findings in which farmers are found to revise crop decisions on short term assessments of the upcoming season (Ingram et al., 2002).

3.4. Yield (Y)

We use the original production function developed by the Food and Agricultural Organization (FAO) (Steduto et al., 2012) to simulate the impact of water shortage on yield. The function is simple, but complex enough for our purposes and relates, for each crop, evapotranspiration to yield through a yield response factor, k_y . It is expressed as: $\left(1 - \frac{Y_a}{V_x}\right) = k_y \left(\frac{ET_a}{ET_x}\right)$. Here Y is yield, *ET* is evapotranspiration, and the subscripts "a" and "x," stand for "actual" and "maximum", respectively. If $k_y = 1$, yield is linearly related to a reduction in crop transpiration due to a water deficit. If $k_y > 1$, the crop is relatively drought intolerant and yield losses are proportionally larger compared to the water deficit. If $k_y < 1$, the crop is relatively drought tolerant and yield losses are proportionally smaller compared to the water deficit.

Rewriting the production function according to the terminology used in this paper results in $(1 - \frac{Y_1}{1}) = \alpha_{Y_1}$ $(\frac{T_1}{\alpha_{H1}})$ for crop 1. Hereby, we normalize the maximum production Y_x to 1. Rewriting the above equation as a function of Y_1 gives equation (4a). Since the FAO function is only valid for ET_a \ge 50% of its maximum value, we introduce a dummy variable, i.e., H = 1 if $T_{1,2} > 0.5 \alpha_{H1,2}$ and H = 0 if $T_{1,2} < 0.5 \alpha_{H1,2}$.

$$Y_1 = -H\left(\left(1 - \frac{T_1}{\alpha_{H1}}\right)\alpha_{Y1} - 1\right)C_1 \tag{4a}$$

For Y₂, the above steps result in:

$$Y_2 = -H\left(\left(1 - \frac{T_2}{\alpha_{H2}}\right)\alpha_{Y2} - 1\right)C_2 \tag{4b}$$

Lastly, total yield, Y, is defined as $Y_1 + Y_2$.

4. The Socio-Hydrology of Smallholders in the Upper Ewaso Ng'iro Basin

4.1. Study Area

The case study area lies on the north western slope of Mount Kenya in the Upper Ewaso Ng'iro river basin (Figure 3). Altitudes range from 2,600 to 1,000 m and, accordingly, mean annual precipitation ranges from 1,050 mm to less than 600 mm. Most of the rainfall falls during two seasons, the long rains (mid-March to mid-June) and the short rains (October–December). The high potential evaporation affects crop production increasingly as one moves away from Mount Kenya (Ngigi et al., 2007).

Water management institutions in Kenya have evolved from a centralized, top-down water permit scheme to a more decentralized system in 2002 that is based on the principles of integrated river basin management (Baldwin et al., 2016). Water in the study region is obtained either through rainfall directly on the land or through access to river water. With the recent wave of immigration to the area, concerns over water scarcity have increased. Irrigation systems, known as community water projects were established, mostly supported by government programs and/or donors (McCord et al., 2016).

4.2. Smallholder Responses to Changing Water Availability

In 2013, a data collection campaign was conducted by Indiana University, Princeton University, and the University of Nairobi to understand how sedentary smallholder farmers are impacted by climate change given the institutional mechanisms in place to govern water availability. Household surveys were primarily





Figure 3. Location of the study area close to Mt. Kenya. The area lies within the Ewaso Ng'iro basin, an upper catchment of the Juba basin (small map). Most households that took part in the interviews are part of community water projects (centroids indicated in black) and receive river water, in addition to rainfall (McCord et al., 2015, 2017). A major market town in the region is Nanyuki. Source maps: Said et al. (2007).

conducted within community water projects. The center-points of these community water projects are shown in Figure 3. Community water projects consist of a variable number of households who all receive water through a network of pipes, ultimately connected to a single intake at the river (McCord et al., 2015, 2017). Some of these communities are experiencing a growth in membership, while others have made the decision to cap the number of households in order to ensure reliable water availability for existing member households. Members pay both initial and monthly membership fees aimed to cover maintenance and management costs. Dell'Angelo et al. (2016) suggest that, based on research in some of the communities, considerable homogeneity exists regarding payment of membership fees, monthly fees, rotating schedules, monitoring regimes, and possible exclusions in instances where rules are broken.

Specially trained enumerators introduced the survey to respondents as a general survey about the function of the water projects and farming practices. Surveys were administered to 750 smallholder farmers, with each survey having a duration of approximately 45 min. Households were selected randomly by proceeding down the water lines and selecting households at specified intervals. The intervals were increased for larger projects to ensure the inclusion of households at the ends of lines and across different lines in the water project. At least 30 households were surveyed in each of the community water projects, which amounted to half of the members in some of the smaller community water projects (see McCord et al., 2015, 2017 for additional information).

The survey data show that farmers experienced several natural challenges in the region including drought, pest, and diseases, temperatures and soil quality. Drought is most frequently mentioned, including by farmers who have the most irrigation water available. Unsurprisingly, drought posed the greatest threat to people who mostly relied on rainfall. Of the 64% or 483 households that indicated drought to be a challenge, almost 40% took measures aimed at increasing water supply (i.e., increase irrigation, increase on-farm storage), while more than 25% took measures aimed at decreasing water demand (i.e., change crop type, change or plant earlier, reduce crop area). Increasing water supply is considered mainly by households who still have irrigation water available and decreases rapidly for those who generally do not have access to irrigation water. Instead, households with no irrigation water access fall back on water demand management strategies and, in particular, to changing crop type. Overall, 53% of the households faced a water shortage



that forced them to change their farming practices. 57% of the households indicated that they have planted different crops in response to this shortage. The survey data also show that the households without irrigation water relied more on off-farm income (51%) compared to the households that had most irrigation water available (10%). When households were asked about crops they still wanted to grow and had not grown before, more than 70 different crop types were mentioned. When asked why, answers clearly showed that the market was an important driver for their decisions, followed by private use. Other reasons mentioned were (all in the order of 1–5%); "despite a lack of water," "short maturing/drought-tolerant properties," "suitable climate," "low labor requirement," "storability," "despite lack of funds to buy a greenhouse," "despite temperatures/climate," "health/dietary reasons," "low water demand," "continuous harvesting." Quantitative information supporting the conclusions drawn in this section can be found as supporting information Table S2.

4.3. Detecting Patterns: Eco-Hydrological Crop Characteristics Along the Rainfall and Irrigation Water Availability Gradient

The survey responses suggest that water availability is an important determinant of crop choices, despite the many constraints farmers face. If this is indeed the case, we expect to see a crop pattern along the water availability gradient with drought-tolerant crops prevailing in the drier areas. Figure 4a shows the main crops cultivated in each community.

To capture socio-hydrological interactions, we are interested in extracting information from each crop type that is relevant from a hydrological point of view. Characteristics commonly used to characterize a crop in (eco-)hydrology include crop coefficient (K_c [-]), days to maturity, root depth, and the yield response parameter (k_y [-]). Here the crop coefficient is a measure of the influence of crop characteristics and average soil evaporation on crop evapotranspiration in comparison to a standard, i.e., evapotranspiration measured at a grass reference surface under standard conditions (Allen et al., 1998; FAO, 2015). In short, a higher K_c implies a higher crop evapotranspiration rate. The yield response factor represents the sensitivity of the crop yield to water deficit (see section 3.4 for further explanation).

Compiling the characteristics from the literature (Murphy, 2010; Seed Co Limited, 2011; Sekiya et al., 2013; Zea mays, 2017) for the main crop types in the area (see supporting information Table S3), we calculated, for each community, mean root depth, mean crop coefficient K_c , mean growth period (days), and the mean yield response parameter k_y . Each crop considered accounts for at least 1% of the area and together the selected crops make up ca. 79% of the potential crop area reported by the respondents in 2013. Of the remaining 21%, ca. 12% is fallow land. The results are shown in Figures 4a–4e. The coloring of each characteristic is such that red coloring is indicative of more drought-tolerant crop features. One would expect to see more red colors (drought-tolerant crop features) when moving toward the light blue areas (low rainfall). This pattern can indeed be observed for the average root depth (Figure 4b) and the crop coefficient K_c (Figure 4c).

Since root depth and crop coefficient, K_{cr} are in line with the pattern we would expect from the prevailing rainfall gradient (Figure 4), we assume that these traits are important in explaining the observed crop pattern. In fact, both characteristics influence the system in a similar way, as they determine the water balance of the plant at any given time. The next step is now to quantify the relationship between the amount of water available, i.e., both precipitation and irrigation water, and crop characteristics. Since irrigation water is not directly measured, but information is available on the number of days per month respondents had irrigation water available (period May 2012 to May 2013), we can obtain an educated guess of the amount of irrigation water applied. To this end, we make assumptions on the irrigation depth applied per irrigation day.

Irrigation water technologies used by the respondents vary from hand methods (buckets) to the use of a water hose or movable sprinklers. While periodic irrigation such as by sprinkler or surface irrigation can result in wetting depths greater than 40 mm (Allen et al., 1998), it is unlikely that these wetting depths are reached by all respondents and/or uniformly on each irrigation day for the entire crop area. Depending on rainfall deficit and evapotranspiration, monthly irrigation water deficits are possible in the range of a few millimeters to a few hundred millimeters (Brouwer et al., 1989). We assume irrigation water depths of 4–8 mm per irrigation day leading to plausible, maximum monthly irrigation depths of 120–280 mm. Mean annual rainfall was taken from nearby weather stations with readings from the early 1960s to 2010, and interpolated by ordinary kriging with a spherical semivariogram. Finally, average water availabilities was





Figure 4. (a) Main crops cultivated in each community. Based on crop type, area cultivated and crop characteristics, community averages have been calculated for (b) mean root depth (m), (c) mean crop coefficient K_c (-), (d) growth period (days), and (e) yield response parameter k_y (-). If crop characteristics were unavailable, e.g., for Rhodes grass and Napier grass, the crop was left out of that particular calculation of the average. Root depth (b) and K_c (c) patterns are rational from a water availability point of view.

obtained by adding mean precipitation to the product of irrigation days and irrigation depths for the period May 2012 to May 2013.

The relationship between water availability and crop pattern is presented in Figure 5. For simplicity, and to be able to relate the data to the modeling framework, we have divided the crops into two categories based on their eco-hydrological characteristics. Crops with mean root depths <1.1 m are considered shallow rooted and therefore drought intolerant, while the other crops make up the drought-tolerant category. The *y* axis represents, in all cases, the percentage of shallow rooted crop of the total crop area. The *x* axes show yearly irrigation days (a), yearly water availability (b), average monthly irrigation days during the long rain season lasting from March until July (c), and average monthly water availability during the long rain season (d). All plots show a consistent increase of the percentage of shallow rooted crops when the number of irrigation days or water availability increases. It clearly matters whether the precipitation gradient is taken into



Figure 5. Shallow rooted crop fraction pattern. Plot (a) shows the average shallow rooted crop fraction versus the mean yearly irrigation days reported by the households. Plot (b) shows the shallow rooted crop fraction versus mean annual water availability (rainfall plus irrigation water). Plots (c) and (d) show similar information, but only for the long rain season (March–July). To convert from irrigation days to irrigation water availability, we assumed a fixed irrigation water depth per irrigation day (4 mm or 8 mm). (a) The household data was grouped per 12–25 days, (b) per 100 and 200 mm for 4 and 8 mm depth, respectively, (c) per 3 days, and (d) per 8 and 15 mm for 4 and 8 mm depth, respectively.

account in addition to water availability due to irrigation. The combination of low precipitation and few irrigation days leads to a very low percentage of shallow rooted crop area (Figure 5d), which did not become apparent when considering irrigation days alone (Figure 5c). Lastly, when the irrigation depth per irrigation day is assumed to be 8 instead of 4 mm, the curve flattens and the higher percentages of shallow rooted crop area are associated with higher irrigation water availability (Figures 5b and 5d).

5. Model Calibration

5.1. Calibration Approach: Trading Space for Time

In order to calibrate the model, such that its settings reflect plausible representative behavior, we compare the model results with the data in Figure 5d, which shows the average crop pattern of farmers that took part in the survey as a function of monthly water availability. Given the limited temporal resolution of the data set, it is necessary to assume that observed behavior in space, i.e., crop patterns along the water availability gradient for the year 2013, may also be observed in time (at the same location) as a response to changes in water availability. Trading space for time rests on the assumption that the observed spatial crop pattern is representative of stationary, coevolved conditions (Peel & Blöschl, 2011; Perdigão & Blöschl, 2014). This assumption is motivated by the fact that the smallholder farmers have lived in the area for around 12 years on average and some more than 30 years. We therefore hypothesize that the current average crop pattern is at least partly a product of a coevolving socio-hydrological system in which farmers have tried to allocate crops and water rationally based on their understanding of and interactions with the environment. We assume that any future change in water availability, for example, due to increased water demands as a consequence of migration into the region (primarily outside the community water projects as communities regulate their members), would induce farmers to alter their crop pattern to reflect the new socio-hydrological conditions. Therefore, for each different water availability, we run the model for a



sufficiently long time for it to reach equilibrium—a point where the available water is sufficient to meet the demands of the crops according to the farmer's management strategy.

While we recognize that there are many different drivers of land and water use decision making acting at the local, regional, and global scales (as illustrated by Blaikie and Brookfield, 1987 and Jones, 2002, for land degradation), we consider our assumption of water availability being of primary importance a plausible one. This is particularly evident when its availability is scarce or its supply unreliable (Jain et al., 2015; Kuru-kulasuriya & Mendelsohn, 2008; Wood et al., 2014).

5.2. Parameter Estimation

Model parameters can be set by taking crop averages or by choosing two representative crops. To guarantee a realistic combination of crop characteristics, we follow the latter approach and select maize and potato as representative crops. Both crops make up a large share of the total production in the area (Figure 4) and differ considerably in terms their drought-tolerance features, including root depth. For comparison, we select medium maturity crops that both have a growing season of ca. 4 months (110–150 days) (FAO, 2015). Based on weighted, average K_c values we expect maize ($K_c = 0.83$) to use more water on average than potato ($K_c = 0.81$) (Allen et al., 1998). Setting α_{H2} to an average 150 mm per month, the maize transpiration rate, $lpha_{H1}$, can be calculated at 153 mm per month. Potential evaporation, eta_{H} , varies between 125 mm per month during the dry season and 150 mm per month during the rainy season (Woodhead, 1968). As we are interested in evaporation rates particularly during the offseason, we use the lower value of 125 mm per month. Since we allow for irrigation water and expect this has the time to infiltrate, we set both runoff coefficients such that saturation occurs; $\varepsilon_H = 0.93$, $\zeta_H = 100$. Maximum water content or total available water (TAW) (mm) can be estimated by $TAW = 1,000(\theta_{FC} - \theta_{WP})Z_r$, where θ_{FC} represents the water content at field capacity (m³ m⁻³), θ_{WP} the water content at wilting point (m³ m⁻³), and Z_r the rooting depth (m) (Allen et al., 1998, Chapter 8). For maize, 80% of its water comes from a depth up to 0.8–1 m, while 100% generally comes from a soil depth up to 1.7 m (FAO, 2015). For potato these depths are 0.4 and 0.6, respectively. The soil in the area consists of silt and sand mixed with clay (Kempen, 2017). For silty clay, $\theta_{FC} - \theta_{WP}$ is estimated at 0.13–0.19 m³ m⁻³ (Allen et al., 1998, Table 19). Taking maximum root depth values, as we are potentially looking at stress situations, and an average of 0.16 m³ m⁻³, the TAW for C_1 is estimated at 272 mm, while for C_2 a correction factor of 0.6/1.7 ($\eta_H = 0.35$) is applied. We set $\kappa_{\rm H}$ to 100 so that the logistic function approaches a step function implying that the farmer will change his water allocation as soon as he perceives this is desirable. For the calibration, we assume that a farmer processes water deficit information similarly for both crops, and that α_{M1} equals α_{M2} , and β_{M1} equals β_{M2} . We set $\alpha_{M1,2}$ to 0.07 per month, so that $M_{1,2}$ is around 1 when the soil is completely depleted (and 0 when long-term saturation occurs). Since we know that a farmer generally bases his decisions on knowledge of the previous year, we set $eta_{M1,2}$ to 0.01 per month so that ca. 90% of knowledge is retained within a year. The crop adaptation parameter, α_{C} determines the speed at which farmers change crop type as a response to their perception of crop water deficits. Various factors are known to influence this process, but much is still to be gained in understanding the rate of adaptation (Burke & Lobell, 2010). In case of a quasi-dynamic stable state, the parameter is of less importance and set to 1 per month. The management parameters, β_{C} and γ_{C} influence water allocation and crop choice. For comparison, the values are initially set to have no influence, i.e., $\beta_C = 1$ and $\gamma_C = 0$. Subsequently, they are calibrated to fit the relationship between C₂ and water availability as depicted in Figure 5d, resulting in $\beta_{c} = 0.4$ and $\gamma_{c} = 0.2$ (see section 5.2). Yield response factors α_{Y1} and α_{Y2} are set to 1.25 and 0.8, following known average values for maize and potato (FAO, 2015).

Precipitation is estimated by taking the lowest mean annual precipitation of 588 mm in the study area as a base value and assuming that this is distributed uniformly throughout the year. In trading space for time, we let irrigation water continuously increase from 50 to 350 mm per month during a very long simulation period (1,000 years) to ensure quasi-stable equilibria. The figures 50–350 mm are based on our earlier estimates of monthly irrigation days multiplied by an irrigation water depth of 4–8 mm per day.

Initial soil moisture values, $S_{1,2}$, are set to 80% of their maximum value, C_2 is set to a low value of 0.05, and memory of drought, represented by $M_{1,2}$, is assumed to be high and their initial values are set equal to 1. An overview of the model parameters used for calibration can be found in Table 1; Figures 6a and 6b, where A refers to the uncalibrated simulation and B to the calibrated simulation.



Table 1

Parameters Used for Model Calibration (Figure 6) and the Sensitivity analyses (Figures 7–10)

Parameter	Units	Meaning	Figures 6a and b	Figures 7 and 8	Figures 9 and 10
Hydrology (5)				
α _{H1}	$(mm month^{-1})$	Max transpiration rate crop 1	153		75–225
α _{H2}	$(mm month^{-1})$	Max transpiration rate crop 2	150		75–225
β_H	(mm month ^{-1})	Potential evaporation rate	125		
δ_H	(mm)	Evaporation depth	24		
ε _H	(-)	Runoff coefficient	100		
ζH	(-)	Runoff coefficient	0.93		
η_H	(-)	Root depth correction crop 2	0.35		
κ _H	(-)	Adjustment speed	100		
φ_H	(mm)	Max soil water content	272		221-321
Memory (M)					
α _{M1}	(month ⁻¹)	Memory encoding rate	0.1		
α _{M2}	(month ⁻¹)	Memory encoding rate	0.1	0.035-0.14	
β_{M1}	(month ⁻¹)	Memory loss rate	0.01		
β_{M2}	(month ⁻¹)	Memory loss rate	0.01	0.005-0.02	
Crop Adapte	ation (C)				
α _C	(month ⁻¹)	Crop adaptation rate	1		
β_{C}	(-)	Management strategy	1, 0.4*	0.2 – 0.8	
γс	(-)	Management strategy	0, 0.2*		
Yield (Y)					
α_{Y1}	(-)	Yield response factor	1.25		
α _{γ2}	(-)	Yield response factor	0.85		
Initial Value	5				
S ₁	(mm)	Soil moisture crop 1	217	217	0.8 φ _H
S ₂	(mm)	Soil moisture crop 2	76	76	0.8 φ _H η _H
M_1	(-)	Memory crop 1	1	1.25, 0.4, 0.2	1.25, 0.4, 0.2
<i>M</i> ₂	(-)	Memory crop 2		0.75, 0.4, 0.3	0.75, 0.4, 0.3
C ₂	(-)	Crop fraction crop 2	0.05	0.15, 0.35, 0.9	0.15, 0.35, 0.9
Exogenous H	luxes				
Р	(mm month ⁻¹)	Precipitation (reported values are mean annual)	588 monthly average	588 generated	588 generated
1	(mm month ^{-1})	Irrigation water	Increasing	12, 25, 210	12, 25, 210

Note. The parameters that have been calibrated are marked with an asterisk (*), the others are preset. Parameters that remain unchanged are not repeated. For Figures 7–10, initial memory values have been adjusted in line with the three irrigation water levels (see sections 6.1 and 6.2). Parameter φ_H varies as part of the hydrosensitivity analysis, which is why a relation is given for the initial $S_{1,2}$ values for Figures 9 and 10.

5.3. Calibration Results

Figure 6 shows the outcome of the two model simulations, referred to as A and B, where in case of simulation A the parameters are all preset, while in case of simulation B the management strategy parameters, β_C and γ_C , are calibrated. As water availability is our variable of interest, this is presented on the *x* axis instead of time. When comparing the simulated fraction of drought-intolerant crop, C_2 , to the observed average crop pattern (second row) for simulation A, we observe that the model overestimates C_2 when water availability is small, while it underestimates C_2 when water is abundant. Considering memory (third row), we see that water and crops are allocated such that drought memories of both crops are equal, i.e., $M_1 = M_2$, independent of water availability. The model results imply that, on average, a farmer values both crops equally and tries to minimize the water deficit of both crops equally.

In case of simulation B, we obtain a better fit when comparing modeled crop fraction to shallow rooted crop data (second row). Interestingly, we see that when water is scarce this behavior is obtained by keeping drought memory M_2 and thus water deficit of crop 2 low, thereby sacrificing crop 1 (third row, M_1 increases). Also the expansion of C_2 with increasing water availability is slowed down in simulation B. When sufficient water is available, this behavior dissipates and eventually reverses. The calibrated behavior thus suggests that, on average, a farmer has a preference for the drought-intolerant crop 2, especially when water is scarce.

The difference in water allocation and crop choice is also seen when comparing soil moisture dynamics (first row) as well as cumulative yield (last row) of both simulations. When comparing simulation B to A, soil





Figure 6. Simulation results for an (A) uncalibrated model and (B) a calibrated model. From top to bottom: soil moisture $S_{1,2}$ (scaled by max water content), drought-intolerant crop fraction $C_{2^{\prime}}$ drought memory $M_{1,2}$ and cumulative yield Y_{cum} (scaled by the maximum of the cumulative yield). The simulations (each lasting 1,000 years) are mapped onto a water availability range from 50 to 350 mm/month. While drought memory of both crops remain close to each other in case of simulation A (third row), drought memory of crop 2 is kept low at the cost of drought memory of crop 1 in case of simulation B, indicating a clear water allocation preference for crop 2 when water availability is scarce. The widths of S in the top plots represents seasonal variability.

moisture level S_2 remains much higher during the entire simulation period in case of B, while soil moisture levels of S_1 are lower at the start of the simulation. Consequently, the cumulative yield obtained from crop 2, i.e., Y_2 , also increases during simulation B in comparison to A.

6. Exploring the Behavior of the Modeled System: Sensitivity Analysis

We first obtain a general idea of model sensitivity by estimating the local effect of the parameters on C_2 using the calibrated model. We use the function sensFun that is part of the R package FME and that estimates the derivative of the corresponding modeled value with respect to selected parameters for each data point (Soetaert & Petzoldt, 2010).

The monthly precipitation input is generated with a simple stochastic model, adapted from Bardossy and Plate (1992). The generation process is divided into two steps. First, a discrete Markovian (Autoregressive lag-1) process is used to simulate the desired number of rainfall years with a monthly resolution. Second, the Normal distributed quantiles of the AR(1) process are transformed into Gamma distributed quantiles, including a nonzero probability for zero rainfall in a given month. Measured rainfall data from the nearby station *Nanyuki MoW* is used to calibrate the autoregressive parameter of the Markov model to the observed lag-1 autocorrelation, as well as to fit the monthly parameters of the Gamma distributions and the



zero-rainfall probabilities. The synthetic rainfall values are scaled by a factor of 0.76 in order to reduce the mean annual precipitation from 777 mm/yr (observed in *Nanyuki MoW*) to 588 mm/yr, in order to match the mean annual precipitation used for the model calibration (see section 4.1).

The crop fraction C₂ turned out to be sensitive to the parameters in the following order: α_{H2} , β_C , β_{M2} , α_{M2} , α_{M1} , β_{M1} , γ_C , α_{H1} , φ_H , κ_H , ζ_H , α_C , β_H , δ_H , α_{Y1} , ε_H , α_{Y2} , η_H . We then selected two parameter combinations to perform a global sensitivity analysis.

6.1. Socio-Sensitivity Analysis: The Effect of a Farmer's Management Strategy and Perceptions Regarding Water Availability

In order to explore the impact of a farmer's management strategy and perceptions regarding water availability on crop choice and water allocation, we perform a global sensitivity analysis by varying the three social parameters the model is most sensitive to, i.e., the management strategy parameter β_{C} , the memory loss rate β_{M2} , and the memory encoding parameter α_{M2} .

Using the Latin hypercube sampling method (McKay et al., 1979), we generate 1,000 near-random samples of parameters (that effectively represent the unique perceptions and decision-making routines of 1,000 farmers). We select three levels of irrigation water *I*, namely 12, 25, and 210 mm per month (indicated by an * in Figure 6b). These quantities are, according to our earlier assumptions on irrigation water depth, equivalent to 1–3 days of irrigation, 3–6 days of irrigation and >26 days of irrigation. We assume that these amounts of irrigation water are available during the growing season for the entire simulation period. We then perform 1,000 simulations over a 50 year time span for each of the irrigation water levels, whereby we use the same generated precipitation series.

 β_c varies between 0.2 and 0.8. A low value implies that the farmer will prioritize water allocation to crop 2 and tries to minimize this crop's water deficit before he allocates water to crop 1, or before he further expands the area of crop 2. When β_c is high, the farmer accepts a higher water deficit of crop 2 which allows him to allocate more water to crop 1, or expand the area of crop 2 earlier.

 α_{M2} varies between 0.035 and 0.14, implying that the rate at which the observation of water deficit of crop 2 is converted to memory is respectively halved compared to the calibrated value (i.e., the farmer does not observe or place importance on soil dryness and so does not commit it to memory/the farmer underestimates the soil moisture deficit) or doubled (the farmer places extensive importance on soil dryness and does commit it strongly to memory/the farmer overestimates the soil moisture deficit). β_{M2} varies between 0.005 and 0.02, implying that between 95% and 78% of drought knowledge is retained after a year. In effect, parameters α_{M2} and β_{M2} influence the way the water deficit for crop 2 is perceived (a stronger encoding of the water deficit and a stronger remembrance, will result in a higher memory of water scarcity).

Figure 7 (columns) shows the outcome of the sensitivity analysis for each level of irrigation water. The first row presents the development of C_2 during the 50 year time span. The median C_2 (thick black line) is located at around 0.25 for the left plot, at around 0.4 for the middle plot, and around 0.9 to 1 for the right plot when a farmer has more than 26 days per month irrigation access. These C_2 values are, as expected, in the same positions identified in Figure 6b (for each of the asterisks see the plot representing C_2 to estimate the C_2 fraction). We furthermore observe that, even when we consider that each farmer has their own perception of water availability (represented by variations in parameters α_{M2} and β_{M2}) and their own management strategy (represented by β_C), clear preference bands have developed for each level of irrigation water (gray area).

To assess the effect of the crop pattern on yields, we plot (second row) cumulative yield, Y_1 , Y_2 , and Y (= $Y_1 + Y_2$), against the equilibrium crop pattern for each of the 1,000 simulations. Here cumulative yield is calculated by summing the yields during each time step and dividing it by the potential yield that could have been obtained during the entire simulation period (when soil moisture levels are maintained at maximum water content). Equilibrium C_2 is calculated as the mean of the C_2 values over the last third of the simulation time to minimize the effect of initial conditions. Generally, it can be observed that higher yields are obtained when more water is available (across columns, from left to right). Looking at the individual plots, we see that the contribution of crop 2 (Y_2 , blue) to overall yield (Y, red) increases, when crop fraction C_2 increases. While for the simulations with highest irrigation water availability, total yields seem relatively insensitive to the equilibrium C_2 , this is not the case for the simulations for which there is less irrigation





1 - 3 days of irrigation per month 3 - 6 days of irrigation per month > 26 days of irrigation per month

Figure 7. Outcome of the sensitivity analysis varying management parameter β_{C_1} memory loss rate β_{M2} , and memory encoding parameter α_{M2} . Each column summarizes the outcome of 1,000 simulations for a different level of monthly irrigation water availability, i.e., 1–3 irrigation days, 3–6 irrigation days and >26 irrigation days per month. Precipitation is stochastically generated but kept the same for all simulations. Row 1: drought-intolerant crop fraction C_2 versus time. The median (bold black line), 25th and 75th quantiles (gray band), and min and max values are presented. Row 2: cumulative yield for Y_1 , Y_2 and $Y (=Y_1 + Y_2)$ versus the equilibrium crop pattern for each simulation. Row 3: histogram showing the marginal distribution of equilibrium C_2 .

water available. In both cases (left and middle plot), there seems to be an optimal range of crop fractions C_2 for which yields are highest. This clearly indicates that some farmers, represented by their own unique combination of a memory encoding rate, memory loss rate, and management strategy, perform better than others. Lastly, a histogram is presented depicting the marginal distribution of equilibrium C_2 , including the median (bold black line). Comparing the bottom row with the middle row, we can conclude that the majority of the simulations are centered at the equilibrium C_2 for which yields are maximum.

To increase our understanding of differences among farmers' perceptions and management strategies on equilibrium C_2 , we plot the simulations for the case of 3–6 days of irrigation (results of middle column, Figure 7) as a 4-D plot. Figure 8a shows equilibrium C_2 (color range) as a function of the socio parameters used in each simulation. We observe that the largest area of drought-intolerant crop (equilibrium C_2 approaches one, blue colors) is observed when management parameter (β_C) is high, memory encoding (α_{M2}) for crop 2 is low, and memory loss (β_{M2}) is high. In this case, the farmer's management strategy is aimed at expansion of crop 2 (by accepting a water deficit for crop 2), and he effectively underestimates the soil moisture deficit, which also leads him (her) to increase the cultivation area of crop 2, ultimately leading to a lower yield.

Since both the memory encoding rate (α_{M2}) and the memory loss rate (β_{M2}) influence the final level of M₂, we are interested in the combined effect of these parameters. We therefore define "perceived water deficit" as α_{M2}/β_{M2} multiplied by $\beta_{M2.calibrated}/\alpha_{M2.calibrated}$. We subsequently plot equilibrium C_2 as a function of management strategy parameter β_C (y axis) and perceived deficit levels (x axis) (Figure 8b). The calibrated equilibrium C_2 and corresponding parameter values are marked in Figure 8b by the vertical and horizontal dashed lines (perceived deficit level equals 1, β_{M2} equals 0.4). Generally, the higher the perceived deficit level larger than one, the farmer overestimates the level of dryness for crop 2 compared to crop 1, and consequently allocates more land to crop 1 than to crop 2, as is also illustrated by the brown colors. The farmer loses money by being too careful. For a perceived water deficit level smaller than one, the farmer underestimates





Figure 8. The effect of perceived water deficit level and management strategy on equilibrium crop C_2 (drought-intolerant crop fraction). Results are shown for 3–6 days of irrigation water availability per month (corresponding to the middle column in Figure 7). (a) The effect of management strategy β_{C_1} memory loss rate β_{M_2} , and memory encoding parameter α_{M_2} on equilibrium C_2 . (b) The effect of management strategy and perceived water deficit on equilibrium C_2 (higher values imply that the water deficit of crop 2 is more strongly perceived). The intersection of the horizontal and vertical lines in plot b marks equilibrium C_2 corresponding to the calibrated parameter combination. (c) Equilibrium memory $M_{1,2}$ associated with equilibrium C_2 levels, plotted against perceived water deficit.

the level of dryness for crop 2 compared to crop 1, and consequently allocates more land to crop 2, as is illustrated by the blue colors. The farmer loses money by being too opportunistic.

Assuming now that every individual perceives the world a little different (Elliott, 2003) and that these differences can be represented by a change in value along the *x* axis (perceived water deficit), we can observe that for each deficit level, a farmer can influence the crop pattern by adjusting his management strategy (moving vertically in Figure 8b). The clusters in color indicate that different combinations of perceived water deficit and management strategy may lead to a similar equilibrium crop pattern. We may therefore conclude (also on the basis of Figure 7) that, even if each farmer perceives the world a little different (effectively underestimates or overestimates water availability), similar (near-optimal) crop patterns can emerge, as a result of the interplay of a farmer's perception and the management strategy he adopts.

Figure 8c shows equilibrium levels of memory (calculated in the same manner as equilibrium values of C_2) associated with the equilibrium C_2 levels and plotted against perceived water deficit levels. The figure shows that memory M_2 generally increases when the perceived crop water deficit is higher. Also, it shows that for a farmer to cultivate crop 2 on most of his land (blue colors), water deficit levels are indeed perceived to be low ($M_{1,2}$ are small).

6.2. Hydrosensitivity Analysis: The Effect of Crop and Soil Characteristics

In order to explore the impact of (eco-)hydrological variation on water allocation and crop choice, we perform a global sensitivity analysis by varying three of the hydrological parameters the model is most sensitive to, i.e., the maximum transpiration rate of crop 2, α_{H2} , the maximum transpiration of crop 1, α_{H1} , and the maximum soil moisture content, φ_{H} . We use the same procedure of generating samples, irrigation and precipitation as for the socio-sensitivity analysis.

We let parameters α_{H1} , α_{H2} vary between 75 mm per month and 225 mm per month. The values are associated with a low evaporative demand (1–3 mm per day) to a high evaporative demand (5–7 mm/d),

respectively (Allen et al., 1998). Parameter φ_H varies between 221 and 321 mm and is informed by the range in soil water content, i.e., 0.13–0.19 m³ m⁻³ (see also section 4.1).

Figure 9 (columns) shows the outcome of the sensitivity analysis for each level of irrigation water. The first row presents the development of C_2 during a 50 year time span. Comparing the three plots at the top, we see that for each of the irrigation levels, a dominant crop pattern (gray band) is present despite variation in evaporative demand and soil water content. The range in C_2 (gray lines, min and max values) seems to be smaller for each plot compared to the range as a consequence of varying the social parameters (row 1, Figure 7).

To assess the effect of the prevailing crop pattern on yield, we plot cumulative yield for Y_1 , Y_2 , and Y against the equilibrium crop pattern for each of the simulations (second row). We use the same method to calculate yield and equilibrium C_2 as before (section 6.1). It can be noted that much more variation in yield is present in comparison to the socio sensitivity analysis (row 2, Figure 7). Since two of the three parameters (α_{H1} , β_{H2}) directly influence the amount of water that is needed to produce one unit of yield, this is a logical outcome. A second look shows that, in case of 1-3 and 3-6 irrigation days per month, most of this variation is due to Y_{1} , while for >26 irrigation days per month the variation disappears. This is due to the management strategy the model is calibrated to. The model was calibrated such that, on average, farmers have a preference for crop 2. Subsequently, a farmer aims to keep M_2 low at all times and much of the expected, natural variation is damped for this crop. In the third case, enough water is available to supply both crop 1 and crop 2 with sufficient irrigation water and variation disappears. In the last row, a histogram is presented showing the marginal distribution of equilibrium C₂, including the median (bold black line). Comparing row 3 with row 2, we might conclude that on the basis of the model's current parametrization, the majority of farmers settle for a safe equilibrium C_2 , whereby marginal yield returns are still increasing if the C_2 fraction would be expanded. In practice, uncertainty exists not only in regards to rainfall but also in regards to irrigation water supply (McCord et al., 2017) and this might also influence the observed pattern.



1 - 3 days of irrigation per month 3 - 6 days of irrigation per month > 26 days of irrigation per month

Figure 9. Outcome of the sensitivity analysis to maximum transpiration rate of crop 2, α_{H2} , the maximum transpiration of crop 1, α_{H1} , and the maximum soil moisture content, φ_H . Each column summarizes the outcome of 1,000 simulations for a different level of monthly irrigation water availability. Precipitation is stochastically generated but kept the same during all simulations. Row 1: drought-intolerant crop fraction C₂ versus time. The median (bold black line), 25th and 75th quantiles (gray band), and min and max values are presented. Row 2: cumulative yield for Y_1 , Y_2 , and $Y (= Y_1 + Y_2)$ versus the equilibrium crop pattern for each simulation. Row 3: histogram showing the marginal distribution of equilibrium C_2 .



To increase our understanding of the effect of (eco-)hydrological variation on water allocation and crop choice, we create a 4-D plot that shows equilibrium C_2 , corresponding to 3–6 days of irrigation water (column 2, Figure 9), as a function of the hydrological parameters α_{H2} , α_{H1} , and φ_H (Figure 10a). We observe that the area allocated to the drought-intolerant crop (equilibrium C_2 approaches one, blue colors) increases when the maximum transpiration rate of crop 2 (α_{H2}) decreases or when the maximum transpiration rate of crop 1 (α_{H1}) increases. The effect of max soil moisture content (φ_H) is small, which might be due to the model formulation as variations in maximum soil moisture content affect both crops proportionally. Also, once the soil becomes depleted, the added effect of extra soil moisture content vanishes.

Given that α_{H1} and α_{H2} are dominant in determining equilibrium C₂, we focus on these parameters in Figure 10b. We plot relative water demand of crop 2 versus a measure of water demand of both crops. Relative water demand is calculated as $\alpha_{H2}/\alpha_{H1} * \alpha_{H1,calibrated}/\alpha_{H2,calibrated}$ and total water demand is calculated as $\alpha_{H1}/\alpha_{H2,calibrated}$ $\alpha_{H1.calibrated} * \alpha_{H2} / \alpha_{H2.calibrated}$. The bold dashed lines in Figure 10b indicate the equilibrium C₂ and corresponding parameters obtained at calibration (relative water demand and total water demand equal 1). We now observe that the area is dominated by crop 2 (blue colors), when the maximum transpiration rate of crop 2 is less than the crop transpiration rate of crop 1 (relative water demand < 1), and when total crop water demand is low. The sequence of feedbacks that is set in motion is the following: when the transpiration rate of crop 2 is low, the average soil moisture level of crop 2 will be higher, memory M_2 will be lower, less irrigation water, l_{2r} is needed to reach a satisfying soil moisture level for crop 2, and the farmer can expand crop fraction C_2 . When crop water demand of crop 1 is also lower, area expansion of crop 2 will occur even faster, since the water that would be used to irrigate crop 1 can now also be used to irrigate crop 2. While the above variations are possible due to variations in evaporative demand of the atmosphere, changes (declines) in α_{H2} , α_{H1} could also come about due to the introduction of new crop varieties with a higher yield per unit water consumption. Following similar reasoning as above, the model suggests that a farmer will adjust the crop pattern such that a new equilibrium C_2 is found and the additional water is again allocated according to his management strategy and perceptions on water availability.



Figure 10. The effect of hydrological variability on equilibrium C_2 (drought-intolerant crop fraction). Results are shown for 3–6 days of irrigation water availability per month (corresponding to middle column, Figure 8). (a) The effect of varying maximum transpiration rate of crop 2, α_{H2} , maximum transpiration rate of crop 1, α_{H1} , and maximum soil moisture content, $\varphi_{h,r}$ on equilibrium C_2 . (b) The effect of relative water demand and total crop water demand on equilibrium C_2 . The intersection of the horizontal and vertical lines in plot b marks equilibrium C_2 corresponding to the calibrated parameter combination. (c) Equilibrium memory $M_{1,2}$ associated with equilibrium C_2 levels and plotted against the degree of total crop water demand.



Figure 10c shows equilibrium levels of memory associated with equilibrium C_2 levels plotted against total crop water demand. The figure confirms the positive relationship between total crop water demand and increasing drought memory. Also, the divergence in drought memory ($M_1 > M_2$) of both crops as total water demand increases can be noted, as a consequence of the farmer's management strategy favoring crop 2 in case there is little water.

7. Discussion

We set out to develop a descriptive, coupled model framework that allows the exploration of farmers' perceptions regarding water availability, water allocation, and crop choice. The model framework aims at capturing the socio-hydrological interactions in a complex agricultural system dominated by smallholder agriculture.

For simplicity, two crops were modeled, a drought tolerant, low demanding crop (crop 1), and a drought intolerant, risky crop (crop 2). We assumed that a farmer's perception of water availability could be represented by the combination of two variables, M_1 and M_2 , where M_1 represents the water deficit perceived for crop 1 and M_2 the water deficit perceived for crop 2. We furthermore postulated that a farmer, despite imperfect knowledge, is able to compare and rank crops in terms of their water needs, i.e., by comparing M_2 to M_1 . He (She) then uses this comparison as the basis of a management strategy to choose crops and allocate the available water. Stepwise, the farmer is able to reach an equilibrium crop pattern given prevailing water availability conditions, but can also depart from this pattern in case circumstances change. While a ratio scale is used to represent differences in M, decisions are simulated on the basis of the actual difference between M_2 and M_1 . To a certain extent, it therefore no longer matters which metric is used as long as it is internally consistent. This is similar to how individuals can measure, judge and act, on the basis of comparisons to unique and internally defined reference points (Elliott, 2003; Öhlmér et al., 1998). Humans have relied on this type of comparisons long before measurement scales were invented (Saaty, 2008).

The model highlights that a multitude of different perceptions to water availability result from how an individual farmer encodes water availability, commits it to memory and retains it for retrieval. These differences in memory, in combination with each farmer's individual management strategy on how he (she) allocates water and chooses crops, are the reason why different crop patterns come about, including patterns that are less optimal. However, the model also shows that, even though different perceptions and management strategies exist, common crop patterns tend to emerge driven by water availability. Moreover, multiple configurations exists that lead to an equilibrium crop pattern that is favorable in terms of yield. The framework therefore is consistent with the theory of bounded rationality, which hypothesizes that humans, who are assumed to have limited cognitive abilities and imperfect information, adopt satisficing behavior (Simon, 1955). The model offers an alternative to, for example, normative approaches in which humans are assumed to choose an optimal outcome considering all possible combinations based on perfect information. Both type of approaches are valuable in designing policy and management actions that aim to shift suboptimal trajectories of socio-hydrological systems toward more desirable directions.

Model results illustrate what might happen if eco-hydrological processes change. For example, if due to a warmer climate crop transpiration rates of both crops were to increase, memory levels of farmers would increase, resulting in an increase in the cultivation of crop 1 (the drought-tolerant crop) to accommodate for the increased water demand. Alternatively, if a more water efficient crop variety were to be introduced, the observed response is a readjustment of the crop pattern such that the additional water is again allocated on the farm, as the farmer, in line with his management strategy, will expand the area of crop 2. By focusing on farmer perceptions to water availability and how this drives decision making, the model is able to capture the rebound effect (Berbel et al., 2015; Sivapalan et al., 2014; Sorrell & Dimitropoulos, 2008). The rebound effect refers to the observation that real water savings due to increases in efficiency are smaller than potential savings, for example, due to additional opportunities of irrigation. Thus if a policy aim is to increase the level of stream flow in the basin, the model suggests that efficiency improvements need to be accompanied by additional regulation aimed at changing the farmer's customary behavior.

To test our model framework, we have calibrated the model on the basis of crop patterns observed in the Upper Ewaso Ng'iro Basin. In addition to simulating the observed crop patterns, its application suggests that the farmers that took part in the survey have, on average, a preference for the more risky, drought-

intolerant crop. For low amounts of water availability, proportionally more water was allocated to the drought-intolerant crop at the expense of the drought-tolerant staple crop. While the results would be plausible in view of the higher market value of the riskier, shallow rooted crops such as potatoes and vegetables (FAO, 2017), and considering that the market is an important driver among respondents, caution is required when drawing conclusions from the case study application. The observed crop pattern is the outcome of many considerations and potential tradeoffs regarding bio-physical factors such as temperature, soil type, pests, and diseases, as well as socio-economic factors, such as wealth, age or education (Tittonell et al., 2010). The model is not built to capture and trace the individual role of each of these factors, but to capture the main socio-hydrological interactions as part of a complex system to improve coevolutionary understanding (Sivapalan & Blöschl, 2015). Also, given the limited temporal dimension of the data set, the model framework could not be used to its full potential. While the "trading space for time" assumption may be used to obtain a first order assessment (Singh et al., 2011), caution is required in its application, especially when extending it to the socio-economic domain. Additional dimensions, such as changing norms and values or cultural aspects within a region, further increase the uncertainty associated with the method. Currently, longer-term, high-frequency data from environmental sensors and farmers is being collected to understand how farmers respond to different types of environmental shocks including droughts. A more comprehensive analysis can be performed when this multiyear data set is available.

The stylized choices to create the model framework have allowed us to focus on the interactions between different system components, and have provided a basic model framework which can be explored further and extended as desired. For example in light of current climate adaptation research the model can be a learning tool to test assumptions regarding farmer behavior, and identify successful strategies. While some studies have suggested that farmers are likely to adapt and have pointed out the potential yield gain that farmers can achieve through adaptation (Kurukulasuriya & Mendelsohn, 2008), the added value of this model lies in the ability to explore different adaptation pathways. If a change in climate were straightforward and could be clearly identified then the adaptation processes could be relatively straightforward. However, if farmers need to adapt to a signal which is highly variable and uncertain, deciding on the moment and speed of adaptation is much more complicated. The model could be used to compare the effect of different adaptation behaviors, given specific (and changing) rainfall characteristics. In this initial version of the model framework, it was assumed that a farmer is able to sense all variations in his environment, incorporate these fluctuations into memory and act on these changes, accordingly. It is however possible that farmers are unable to notice incremental changes in their environment, and instead are more sensitive to abrupt changes, so-called triggering or focusing events (Beratan, 2007; Risbey et al., 1999; Smit et al., 1996). Moreover, farmers might be aware of changes in their environment, but delay their response or not respond at all. Lastly, memory itself is likely to be subject to different types of forgetting, distortion or biases (Schacter, 1999). The model could be a tool to evaluate the consequences of these differences in behavior that result from limitations in cognitive ability or from explicit choices of how to respond under different climatic changes. Besides, knowledge and system understanding are not static but evolve through time. Currently, the model maps a variety of different perceptions and behaviors, and therefore has the ability to represent many different types of farmers. A logical step would be to extend the model to include learning such that behavior can change endogenously (like, e.g., Le et al., 2012, who incorporated secondary loop learning in their land use model). In this regard, other sources of information, such as social learning through social networks are likely to be important as well (Pahl-Wostl, 2007). At the same time, further research is needed that maps the actual perceptions of farmers in relation to their management strategy, to better understand under which circumstances water deficits are over-estimated or underestimated potentially resulting in suboptimal crop patterns. Through such work, model assumptions can be further validated, resulting in an improved knowledge basis that can be used to support farmer decision making through developing appropriate water policies.

8. Conclusions

We have presented a novel, socio-hydrological model framework that conceptualizes the interactions between a farmer and his hydrological environment, thereby focusing on water allocation and crop patterns. We have shown that the model is able to simulate the general crop pattern present for smallholders, who are members of community water projects, in Kenya's Upper Ewaso Ng'iro. We have explored how



different perceptions of water availability could impact water allocation and crop choice, and how a farmer, given his perceptions and management strategy, responds to changes in eco-hydrological characteristics. We find that different perceptions may lead to different crop patterns, but also that similar, near-optimal crop patterns can emerge. The framework therefore is consistent with the theory of bounded rationality, which hypothesizes that humans who are assumed to have limited cognitive abilities and imperfect information adopt satisficing behavior. Through focusing on farmer decision making the model also captures the rebound effect, i.e., as additional water becomes available through the improvement of crop efficiencies it will be reallocated on the farm instead of flowing downstream, as farmers will adjust their water allocation and crop pattern to the new water conditions. The model may serve as a framework to understand the potential impact of climate change on the socio-hydrological system, to simulate and test various assumptions regarding farmer behavior and to evaluate policy interventions.

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Acknowledgments

We would like to acknowledge financial support from the Austrian Science Fund (FWF) as part of the Vienna Doctoral Programme on Water Resource Systems (DK W1219-N22). We also gratefully acknowledge support from the U.S. National Science Foundation (grants SES-1360463, SES-1360421, and BCS-1115009). We thank members of the Ostrom Workshop and Johanna Grames for discussing initial versions of this work, Gemma Carr for her valuable feedback and three anonymous reviewers for their comments and suggestions. The authors declare no conflict of interest. The data used in this paper are available in the cited references, figures, and supporting information.

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