FINAL

Simulating small-scale agricultural adaptation decisions in response to drought risk: An empirical agent-based model for semi-arid Kenya

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Keywords: agent-based model, drought adaptation, drought risk, adaptive behavior, adaptation decisions, socio-hydrology

Supplementary information

Supplementary Material

ODD+D protocol (following Müller 2012) of the presented model

Overview

Purpose: The model is designed to disentangle complex adaptive behavior in an agricultural drought risk context. The multi-disciplinary modelling approach is rooted in quantitative socio-hydrology framework', where the human system both influences and adapts to the changing physical agricultural drought environment, and adopts an agent-based approach to deal with heterogeneity in adaptive behavior of smallholder households. Understanding the two-way feedback between households' adaptation decisions and maize yield losses over time will help optimize future drought impact estimations and allow for the testing of drought management policies.

State variables and scales: The model runs over a time span of 30 years (1982-2012) with a 10 year initialization run. Crop growth is simulated with daily time steps (during the MAMJ and ONDJ growing seasons), while adaptation decisions are made once a year (September). Household level farm fields in Eastern Kenya (Kitui, Machakos, Makueni) with an average size of 0.6ha represent the spatial unit of the model, on this level agricultural water management decisions (adaptation) interact with rainfall variability (drought hazard).

There are two types of agents in the model: small scale farming households and agricultural fields. The state variables of households are represented by several livelihood indicators, including; household demographics, human resources, agricultural resources, financial resources, and psychological factors such as change attitude. Agricultural fields are represented by spatially explicit land patches and have a land owner, weather information, land use and water management measures. Exogenous to the model, there is the farm extension service, in which randomly selected farming households receive information on agricultural water management practices.

Process overview and scheduling: Smallholder households grow maize on their fields, which yields according to their agricultural water management and the current weather conditions. Harvest is mainly consumed by the households themselves; extras are sold and shortages are purchased. After droughts or consistent low yields, smallholder households might decide on new agricultural water measures, adapting to the high rainfall variability. This adaptive behavior is modelled using different theories (three scenarios). The eventual adoption of such measures will affect their future chances on food insecurity and poverty. Household agricultural management practices and household food security are the models' dependent variables. Besides, also the poverty rate and average maize yield are tracked over time.

In the presented case study, we consider relatively isolated areas, less subjected to globalized market systems but more vulnerable to food insecurity (Nyariki and Wigings, 1997). Maize price is variable following the total amount of locally produced maize to replicate the observed price volatility (data from FEWSnet) during years of reduced production.

As detailed impact assessments are very location-specific and effective adaptation depends on the understanding of drought risk at scales close to which decisions are made, the model encompasses 1000 farming households and the connection between the crop water model and the human adaptation model occurs in a sequential approach on the spatial unit of the farm fields of each household. The model is only partially spatially distributed - there is a social space in which networking happens, but no physical space as biophysical conditions are the same for all areas.

Design concepts

Theoretical and empirical background: Three adaptive behavior scenarios are analyzed, with increasing complexity. A 'business as usual' scenario with no changing drought adaptation measures is tested, characterizing the 'fixed adaptation' approach. The conventional Expected Utility Theory (von Neumann and Morgenstern, 1944) represents the widely-used economist's assessment of choice under risk and uncertainty. Simulating bounded rational rather than economic rational adaptation decisions, the Protection Motivation Theory (Rogers, 1983) is used as a way to include psychological factors in the heterogeneous adaptive behavior of smallholder households, as it is often stated that Kenyan households' behavior is bounded rational and embedded in the economic, technological, social and climatic context of the farmer (Wens and Johnson 2019; Adger et al. 2007; Johansson et al., 2013).

Individual decision-making: In the first scenario, no decisions are made. In the second scenario, the expected utility of each of the adaptation measures is weighted. Each season, households adopt the measure with the best benefit-cost ratio– if the costs of action are larger than the costs of inaction, and if the initial implementation costs are affordable.

The third scenario explores a more empirical, complex behavior. In this scenario, factors influencing the adoption of drought adaptation measures can generally be categorized into extrinsic factors and intrinsic factors. Extrinsic factors include the social and natural environment in which households exists. This steers a households' perception of the drought risks they face (Risk Appraisal). For example, experiences of historic droughts affects individuals' evaluation of drought risk leading to a biased drought risk judgement (e.g. Singh and Chudasama 2017; Keshavarz & Karami 2014). Generally, more vulnerable households have greater risk perceptions (van Duinen et al. 2016). Besides, access to extension services (field demonstrations, farmer trainings) - used as primary source of information by 30%-, and other sources of information sharing (i.e. through the social network (18%) or NGOs (10%) can have profound effect on whether or not individuals take proactive action (Kitinya et al., 2012; Shikuku, 2017; Haer et al. 2016). Also age, gender and education can play a role (Burton 2014)

Knowing the risk and knowing how to or being able to respond to the risk are not the same, as one should believe a measure will be effective, be convinced that one has the ability to implement the measure and be able to pay reasonable costs (Van duinen). Financial or knowledge constraints may limit economic rational decisions. Also the perceived ability to do something (Coping Appraisal) influences the decision making process (Esner 2012, Eiser 2012). This coping appraisal can be subject to intrinsic factors such as education level, sources of income, farm size, family size, gender, confidence and beliefs, risk-aversion, and age (Shikuku, 2017; Okumu, 2013; Eisner 2012, Van duinen, Dang et al 2014; Zhang et al 2019). In order to understand the observed adaptive behavior of Kenya's smallholder households, it is critical to incorporate such social-economic factors in the decision-making framework of drought – adaptation models (Van duinen et al 2015; Keshavarz & Karami 2014; SRezael salmani 2017; ingh and Chudasama 2017; O'Brien et al., 2006; Maddison, 2007; Adger et al., 2009; Jones and Boyd, 2011; lalani et al 2016; Maddison 2007; Gbetibouo 2009; Deressa et al. 2011; Mandleni and Anim 2011; Wheeler et al. 2013; Gebrehiwot van der veen, Keshavarsz 2016).

Learning: Often, initial decisions, made by a few, can grow into large collective actions, either through government incentive or social networks (Willy et al 2013, Ertsen et al.,2013; Holman et al., 2018). In the third scenario, households interact with their neighbors through traditional forms of labour exchange, cooperatives, pioneer households' and family ties; shaping risk awareness and response attitude (Okumu 2013, Shikuku 2017, Nkatha 2017). Such group membership can enhance social learning and knowledge spill over which influences people's adaptation intention and choice of specific measures (Tongruksawattana 2014; Below et al 2010). In the model, this translates to individual risk perception changing in the direction of the mean risk perception within individuals' social network (Haer?). Besides, households that do not regularly receive extension services, are limited to only implement measures that more than 2 of their neighbors have installed.

Individual sensing: Following the socio-hydrologic framework, households with bounded rational behavior (scenario 3) are embedded in and interact with their social and natural environment. Changes in rainfall patterns during growing season will change households' risk perception; drought memory will influence the adaptive behavior of these households.

Individual prediction: In the third scenario, households receiving extension services have the capacity to predict the average yield gain of adopting a new adaptation measure, which will influence their coping appraisal. Households without this access will predict the yield gain based on the extra yield of their neighbors with the considered adaptation measure.

Interaction: Smallholder households learn from the other households in their social network about the implementation and benefits of drought adaptation measure through pioneer households' and family ties (Below et al 2010; Shikuku 2017). In the third scenario, social interaction is explicitly modelled. Interactions with neighbors shape risk perception – the individual perception moves in the direction of the social network average – and also shape response attitude – households with no access to extension can only adopt measures already implemented by neighbors.

Collectives: In the third scenario, households are either more self-oriented, discussing matter with 10 neighbors, or group-oriented, sharing knowledge within a group / collective of 30 neighboring households. Group membership (traditional forms of labour exchange, cooperatives, …) can enhance social learning and knowledge spill over; Often, initial decisions, made by a few, can grow into large collective actions, either through government incentive or social networks (Ertsen et al.,2013; Holman et al., 2018).

Heterogeneity: Household agents are heterogeneous in terms of state variables (i.e. farm size, household size, assets), and agent categorization (certain- knowledgeable or uncertain) (Shikuku 2017, Asfaw et al 2012). Moreover, in the third scenario, households can be inclined to adopt new technology or can be conservative (attitude-towards-change). Okumu (2013), Shikuku (2017) – among others - found that state variables such as age, gender, education of the household head and the household size have significant effects on this risk- attitude.

Stochasticity: During the initialization, the household attribute values are derived stochastically within the uncertainty range values based on the survey data. For every subsequent time loop of the simulation, a random number between 0-1 is drawn for each household; if this is lower than their adaptation intention (also between 0-1) and the household is able to pay for the measure; then the household adopts it. This way, we account for non-included factors introducing uncertainty in adaptive behavior such as beliefs, physical health, ambitiousness etc. of the households. Moreover, also a stochastic perturbation is added to the Maize yield per farm as calculated through Aquacrop – this to include effects of pests and diseases on the income and food security of farming households.

Details

Implementation Details: The model is coded in R, which is able to link the two sub models in Netlogo (the adaptive behavior sub model) and Matlab (AquacropOS).

Input: The setup of the model is a result of participatory concept mapping with researchers and students of SEKU University, technical advisors of Kitui County department of water, agriculture, livestock and fishing, experts from SASOL foundation and 5 pilot households that have example farms for agricultural extension. The input data for the decision model was obtained from a survey on agricultural drought risk to smallholders in the case study area (Wens, 2019). Survey data includes a short questionnaire among employees of the Kenyan national disaster coordination units (n=10), semi-structured expert interviews (n=8) with NGOs, governmental water authorities and pioneer farmers in the Kitui district in Kenya, and an in-depth questionnaire among 250 smallholder farmers in the central Kitui. Extra information is derived from a household surveys in 2000, 2004, 2007 and 2010, conducted by the Tegemeo Agricultural Policy Research Analysis (TARAA) Project of the Tegemeo Institute. The project collects comprehensive information on rural households including, among others, demographic information, information on agricultural practices, business and informal labour practices, decision making, household assets and consumption in different counties in Kenya. Besides, the model initialization draws heavily from reports of CIAT (Climate-Smart Agriculture in Kenya), FAO (The economic lives of smallholder households), IFPRI and the government of Kenya (County integrated development plans), CCAFS (Baseline Survey Indicators for Makueni/Wote, Kenya.), and from research (characterization of Maize producing households in Machakos and Makueni Districts) of Muhamad et al. (2010).

Sub models: The FAO crop-water model Aquacrop OS (coded in Matlab© by Tim Foster (Foster et al.)) calculates seasonal crop production, based on hydro-climatologic conditions provided by the climate data and based on the agricultural management of the households. The agent-based model in which farming households decide on their drought adaptation measures, is coded in Netlogo®, a language specialized in ABMs; and is created by the authors.

Initialization: The weather situation from 1980-1990 is replicated to mimic a period pre 1980; which is used as initialization phase where households initialize their risk perception and coping appraisal in the third scenario. The initial setup values are based on reports / surveys from the area (Tegemeo Dataset 2000,2004,2007,2010, and own surveys from 2019 (250 farmers)). The socio-economic household characteristics are summarized in table 3, while the bio-physical field characteristics are summarized in table 4.

Table 3. Basic socio-economic characteristics of households – INPUT ABM. Mainly based on own survey in Kitui (2019) among 250 agro-pastoralists in central Kitui.

Household characteristic	Average value
Farm characteristics	
Farm size	5 acres
Land under maize	Between 0.3 and 1.3 ha, mean 0.6
Demography:	
Life expectancy	59
Average age	45
Household size	5.9
Number of years education	+- 6 years
Finances	
Average assets	365USD +- 100
Farm income	+- 150 USD(even less in the dryer areas)
External income	+- 250 USD, variable in time
Average food expenditure	+-100 USD
Average other expenditure	+-130 USD
Fixed costs field per hectare	+- 110 USD / ha
Average maize consumed	103kg per adult household member
Maize price	32.9 ksh per kg on average – 0.35 USD
Costs of measures	Installation (maintenance is 10%)
Mulch	15 USD per ha , every year
Fanya juu	250 USD / ha
Well	750 USD
Irrigation infrastructure	1000 USD / ha

Table 4. Basic hydrologic, climate and crop characteristics of farm fields – input AQUACROPOS. Mainly based on Wamari et al. 2015 and Ngetich et al 2012

Environmental parameter	Average value
Onset for 1st growing season	Oct 28
Onset for 2nd growing season	April 7
Average maize harvested	+-600kg; +- 11 bags
Annual precipitation	942mm
Plants per ha	44000