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A coupled agent-based model to analyse human-drought feedbacks for agropastoralists in dryland regions

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Drought is a persistent hazard that impacts the environment, people's livelihoods, access to education and food security. Adaptation choices made by people can influence the propagation of this drought hazard. However, few drought models incorporate adaptive behavior and feedbacks between adaptations and drought. In this research, we present a dynamic drought adaptation modeling framework, ADOPT-AP, which combines socio-hydrological and agent-based modeling approaches. This approach is applied to agropastoral communities in dryland regions in Kenya. We couple the spatially explicit hydrological Dryland Water Partitioning (DRYP) model with a behavioral model capable of simulating different bounded rational behavioral theories (ADOPT). The results demonstrate that agropastoralists respond differently to drought due to differences in (perceptions of) their hydrological environment. Downstream communities are impacted more heavily and implement more short-term adaptation measures than upstream communities in the same catchment. Additional drivers of drought adaptation concern socio-economic factors such as wealth and distance to wells. We show that the uptake of drought adaptation influences soil moisture (positively through irrigation) and groundwater (negatively through abstraction) and, thus, the drought propagation through the hydrological cycle.

KEYWORDS

drought, feedbacks, agent-based model (ABM), socio-hydrology, agropastoralists, drylands

1. Introduction

The impacts of drought on agropastoral communities in Eastern Africa have increased over the past four decades (Haile et al., 2019), including failure of the last four consecutive rainy seasons (Ellerbeck, 2022). Droughts are extreme events characterized by a deficit in water availability. Their typically long duration and large spatial extent affect surface and groundwater resources and water quality, leading to ecosystem damage

and socio-economic impacts (e.g., reduced crop or livestock production and insufficient access to clean water). These effects threaten the livelihoods and lives of agropastoral communities. Eventually, it can lead affected communities to adopt adverse coping mechanisms, placing them in need of emergency assistance (WFP, 2019). Therefore, proactive drought adaptation is key to preventing or mitigating the impacts of drought and preparing for a potential increase in extreme drought under climate change (Pörtner et al., 2022).

Adaptation to drought among agropastoral communities is challenging because of the complexity of drought. Drought can develop as a result of natural drivers (e.g., lack of precipitation) and human influences such as water abstraction and deforestation (Van Loon et al., 2016). Furthermore, interactions between drought and society are multifaceted, as social perceptions and human responses to drought impacts vary significantly between individuals and communities (Wang et al., 2016). In addition, drought adaptation strategies in some sectors (e.g., agriculture and energy) can increase the risks for other systems (e.g., ecosystems) (Christian-Smith et al., 2015). Moreover, negative feedback loops such as the supply–demand cycle, where increased water supply accelerates water use, can offset the initial benefits of reservoirs. Such negative feedback loops complicate drought adaptation and risk management (Di Baldassarre et al., 2018). However, two-way feedbacks between hydrological dynamics and human adaptive behavior are often neglected in drought analysis (Montanari et al., 2013; Bierkens, 2015; Van Loon et al., 2016; Wens et al., 2019). Consequently, inadequate representation of these feedbacks can lead to a severe shortcoming in drought assessments and the potential failure of drought or water management strategies (Sivapalan, 2015).

Agent-based models (ABMs) can capture feedbacks caused by heterogeneous human decision-making processes. An ABM is a computational model that can simulate complex systems composed of individual components (known as agents) interacting within an environment through prescribed decision rules (Farmer and Foley, 2009). In the field of water resources, agents can represent diverse actors (farmers, government organizations, etc.) who interact with each other and their environment (e.g., land and water resources) (Kaiser et al., 2020). ABMs are developed to assess the emergent properties and macro-scale processes originating from dynamic individual behavior. Instead of modeling the generic effect of top-down policies, ABMs can simulate the aggregated effects of individual bottom-up decisions, which makes them suitable for analyzing human–water interactions in complex socio-hydrological systems (Troy et al., 2015).

Various studies have used ABMs to investigate interactions between people and water security. In some studies, ABMs have been coupled to an agricultural, water balance or hydrological model (Swamikannu and Berger, 2009; Huber et al., 2019).

Other studies have focused on the adaptation behavior of agents in response to drought (Hailegiorgis et al., 2010). Van Oel and Van der Veen (2011) used an ABM to assess the effects of basin closure in the Lake Naivasha region in Kenya. The authors demonstrated the effects of government interventions such as payments for environmental services on water availability. Dobbie et al. (2018) developed an ABM to assess food security for communities in Malawi. However, few studies have assessed the dynamic adaptive feedbacks of agropastoralists coping with drought. In addition, most of the existing ABMs integrating hydrology and human behavior lack a foundation in behavioral theories and a link to spatially explicit hydrological models that can capture dryland processes in Eastern Africa. Therefore, Wens et al. (2020, 2022) developed ADOPT, an ABM for drought adaptation by individual farmers in Kenya, using Protection Motivation Theory (PMT). This theory originates from the domain of psychology and describes how people behave under risk. However, this model focused on crop farmers rather than agropastoralists and is not spatially explicit.

In this research, we further develop (Wens et al., 2020) ADOPT model into a conceptual socio-hydrological framework for agropastoralists (ADOPT-AP) to capture drought–human interactions in dryland regions. We modify ADOPT by coupling it to DRYP (Dryland Water Partition model), a new hydrological model developed for dryland regions (Quichimbo et al., 2021). Additionally, we implement decision rules specifically for agropastoralists' livelihoods. This approach allows us to understand the dynamic feedbacks between drought adaptation and drought hazard in drylands. The modeling framework is applied to a catchment in Kenya. ADOPT-AP uses empirical data from existing surveys to parameterise the model's human behavior component and hydrological data to parameterise the hydrological component. Note that this research does not present a fully calibrated and validated model, rather a conceptual framework and its potential capabilities to explore and understand human–drought feedbacks.

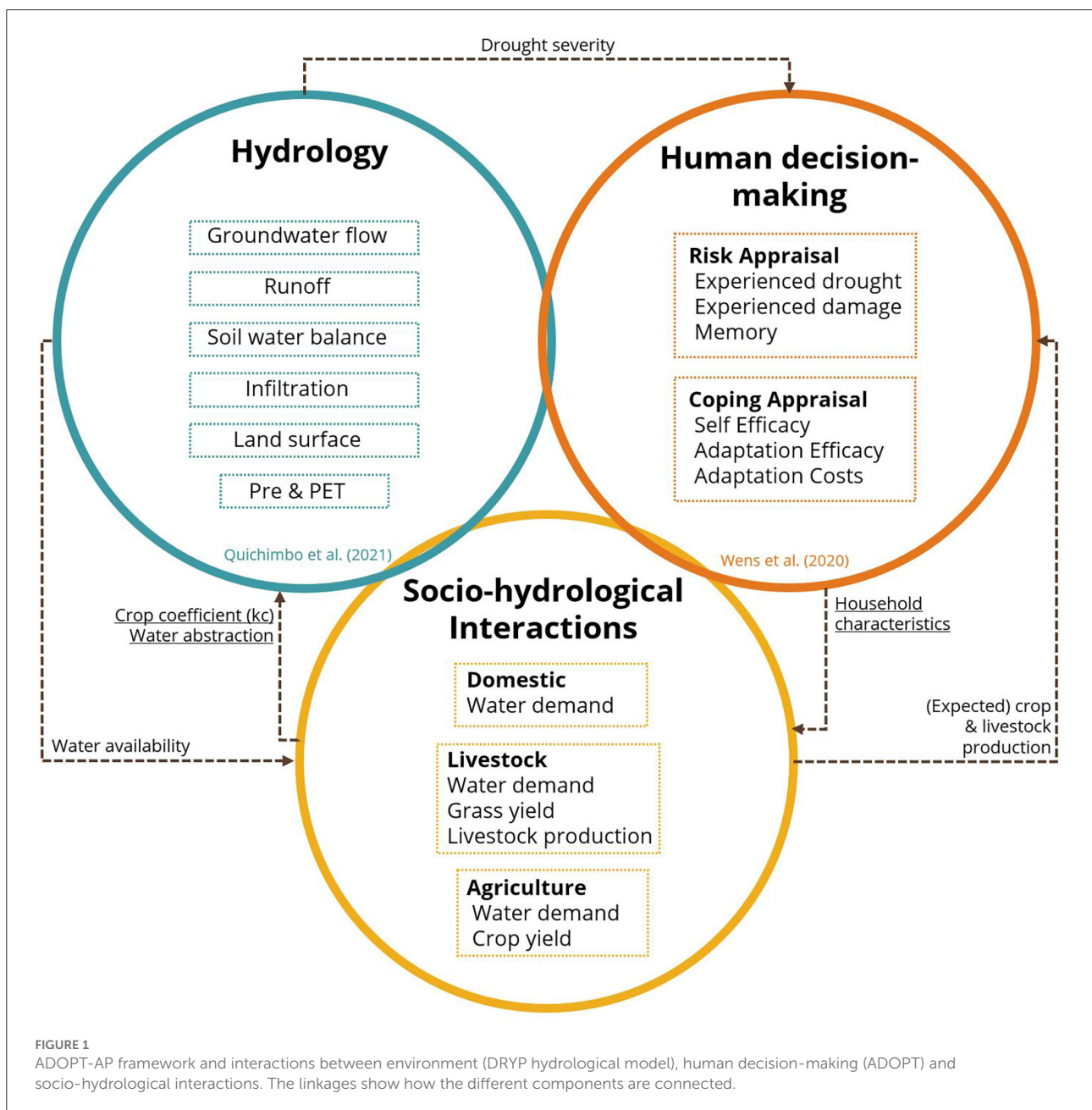
2. Methods

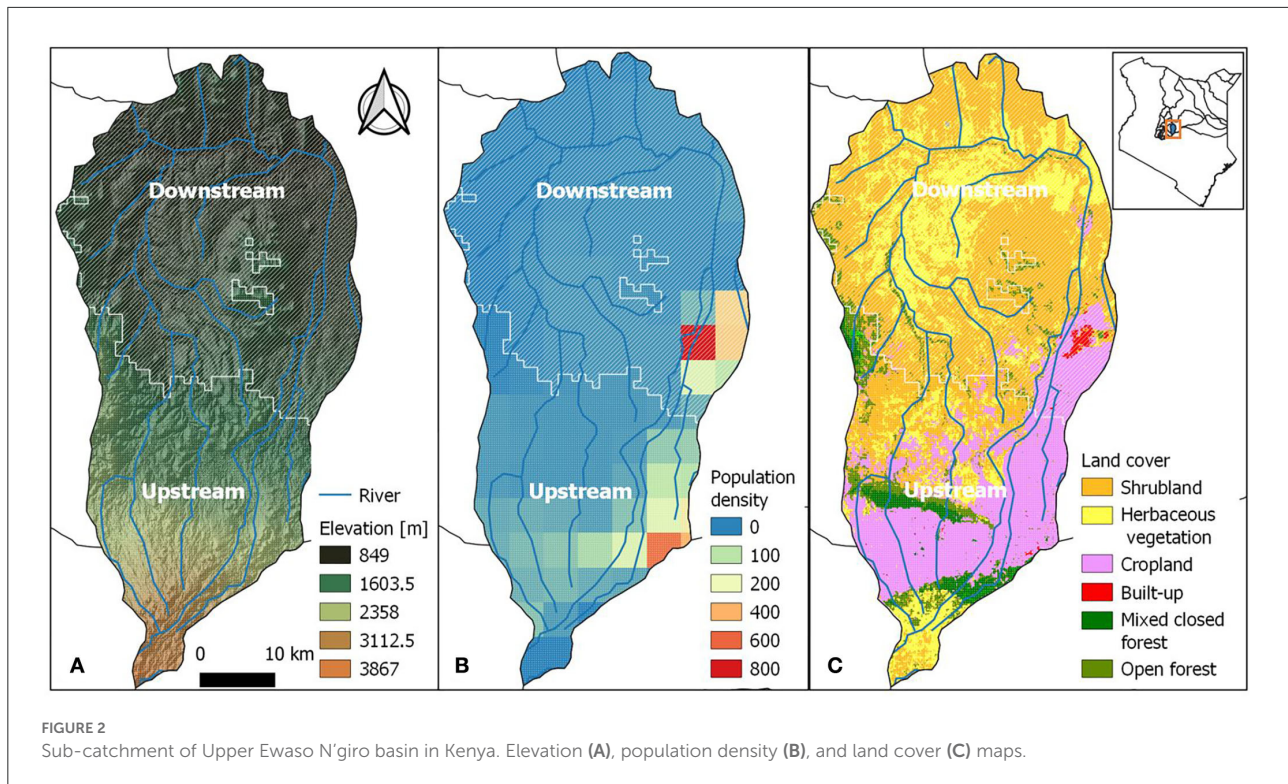
An overview of the proposed model framework can be found in Figure 1. ADOPT-AP consists of three parts: (1) the environment, (2) socio-hydrological interactions and (3) human decision-making. The modeling framework integrates the DRYP hydrological model (Quichimbo et al., 2021) with the human behavior component of the ADOPT model (Wens et al., 2020) and is built upon the ABM package Honeybees (de Bruijn et al., 2022). ADOPT-AP has been designed to simulate individual drought responses by agropastoralists (the *agents*) within their *environment* represented by the hydrological model output. *Agropastoralists* are here defined as households that grow crops, tend livestock or a combination of both as their

main livelihood. The *socio-hydrological interactions* represent the feedbacks between agropastoralists and environmental land-water processes (i.e., water demand and grass and crop yield) of the drylands in Eastern Africa. *Human decision-making* is represented using PMT, a theory of decision-making under threat (Maddux and Rogers, 1983) and implemented into the model by quantifying the factors that drive the intention to adapt to drought risk.

The agropastoralists make adaptation decisions over time. The model includes ~2,500 agents with a heterogeneous set

of characteristics. The spatial resolution is 1 by 1 km² and the temporal resolution is 1 day. Each grid cell has one agent making decisions and changing the environment. Since there is one agent for every grid cell, an agent can represent multiple households, depending on the population density map (i.e., if 100 people live in a cell, the agent represents 100 individuals). Following the Overview, Design Concepts and Details + Decisions (ODD+D) protocol (Müller et al., 2013), a detailed overview of the modeling structure and scheduling is given in the [Supplementary material](#).





2.1. Case study: Upper Ewaso N'giro basin in Kenya

The model was applied to a sub-catchment of the Upper Ewaso N'giro basin in Kenya (Figure 2). Mount Kenya, in the southern part of the catchment, is the local water tower. The catchment and its agents were divided into two parts based on elevation: upstream above 1,300 m and downstream below 1,300 m. These two parts have discernible differences in received precipitation, land use and livelihoods. We later compared these different agent groups in the analysis, an advantage of using ABMs. The upstream part of the catchment is dominated by cropland and forest and has a relatively high altitude. The main livelihood is agropastoralism (i.e., combining agricultural and livestock practices). The downstream part of the catchment is predominantly covered by grassland and scrub, with pastoralism as the dominant livelihood (FEWS NET, 2011). It is a drier lower-lying area (Figure 2).

2.2. Environment: Dryland water partitioning model, DRYP

DRYP is a process-based distributed hydrological model developed to capture the main hydrological processes in dryland regions (Figure 1, Environment). Precipitation and potential

evapotranspiration are the model's primary driving variables. Precipitation is divided into infiltration and surface runoff, depending on soil moisture conditions. Soil moisture can evaporate directly, be transpired by plants or percolate to the subsurface reservoir (diffuse recharge). Runoff is routed to streams, following the topography. Stream water can be infiltrated through the streambed (transmission losses) if the water table is below the stream's bottom elevation. Conversely, groundwater is discharged into the streams as baseflow if the water table is above the channel stream stage. Transmission losses contribute to the development of ephemeral streams and can recharge subsurface reservoirs, a process known as focused recharge. Water from groundwater aquifers and surface streams can be abstracted by individuals and communities. In addition, irrigation water can be applied to the land (modeled as additional rainfall). Human-induced land use changes are included by altering the crop coefficient (k_c), influencing actual evapotranspiration. A more detailed description of the model can be found in Quichimbo et al. (2021).

2.3. Socio-hydrological interactions

The agents are (groups of) agropastoral households that have livestock and cropland. The agents can change the environment through the socio-hydrological interactions of

water and land use for *domestic, agricultural* or *livestock* purposes. Water can be abstracted from the environment for all three purposes directly from a river or groundwater abstraction point. Groundwater abstraction points are randomly distributed across space due to a lack of information about their number and location. The river network is based on a representation of the catchment (Figure 2).

2.3.1. Domestic

The domestic water demand for households in each cell is calculated for each (daily) time step. It is assumed that households abstract water from the nearest available source: either surface water from a river or groundwater from an abstraction point. Domestic water demand is calculated by multiplying the number of people in a grid cell by the daily water requirement per person (50 L/day per person in rural areas Oageng and Mmopelwa, 2014). Actual water abstraction is limited by the water available in the nearest (non-dry) water source (either river or well).

2.3.2. Agriculture

When households have adopted the adaptation measure “apply irrigation” (not further differentiated in types of irrigation measures), water demand for irrigation is based on the soil moisture deficit (SMD) during the crop growing season, calculated as follows:

$$SMD = D_{root} \cdot (\theta_{fc} - \theta) \quad (1)$$

where D_{root} is the rooting depth (mm), θ is the water content (-) and θ_{fc} is the water content at field capacity (-). Irrigation demand is derived by multiplying the SMD by the sum of the irrigated land area for each household in a cell. In the sensitivity analysis a variable factor (default of 1) can multiply the SMD, and can represent different types of irrigation methods and their water-efficiency (e.g., drip or furrow irrigation).

Crop yield is calculated based on the ratio between the crop’s actual (AET) and potential evapotranspiration (PET). This calculation follows Siebert and Döll (2010) and is slightly more detailed than the FAO approach (Allen et al., 1998). If the ratio is 1 (AET = PET), crop yield is at its maximum, while a lower AET reduces crop yield. The crop coefficient k_c , with the reference evapotranspiration, determines a crop’s PET, which indicates how much the crop would evaporate, assuming it is healthy and well-watered. The crop coefficient depends on the crop type and its development stage (Allen et al., 1998). We used crop factors for maize and cassava from Siebert and Döll (2010). Actual evapotranspiration indicates how much the crop evaporates based on the current water availability. Crop yield is then calculated by multiplying the maximum (irrigated) yield,

following Siebert and Döll (2010):

$$Ratio_{crop_yield} = \begin{cases} 1 & \text{if } a \frac{AET}{PET} + b > 1 \\ aP1 + b - \left(P1 - \frac{AET}{PET} \right) * \frac{aP1+b}{P1-P0} & \text{if } P0 < \frac{AET}{PET} < P1 \\ 0 & \text{if } \frac{AET}{PET} \leq P0 \\ a \frac{AET}{PET} + 1 & \text{else} \end{cases} \quad (2)$$

$$Yield_{crop} = Ratio_{crop_yield} \cdot Yield_{crop_max} \quad (3)$$

where a, b, P0, and P1 are crop-specific parameters statistically derived by Siebert and Döll (2010).

2.3.3. Livestock

Households own livestock (L_t) which they usually herd at home. However, livestock can graze in a different location when insufficient grass or water is available at home. At the destination location, livestock drink water and graze. Livestock water demand is calculated by multiplying the number of livestock in a grid cell by the daily water requirement per livestock type (Table 2).

Livestock grazing and reproduction are based on the available grass. To simulate grazing, we followed the FAO Irrigation and drainage paper No. 56 (Allen et al., 1998) (Eq. 4). We estimated the grass yield in a grid cell by scaling down the maximum attainable grass yield in that cell using the ratio between AET and PET and a yield-response factor. Grass yield was not computed in urban or cropland grid cells:

$$G_{yield} = 1 - K_g \left(1 - \frac{AET}{PET} \right) \cdot G_{max_yield} \quad (4)$$

where K_g is a yield-response factor [-], which indicates how a crop responds to a reduction of AET vs. PET averaged over the growth period.

Livestock production (number of animals, L_t) is a function of grass yield G_{yield} and calculated on yearly basis (Lopez, 2008; Pande and Savenije, 2016). We assumed that no livestock are bought or sold, as this is not common practice in some East African cultures (Watson and Binsbergen, 2006):

$$L_t = \max \left(L_{t-1} + \left(r_L \left(1 - \frac{L_{t-1}}{K_L} \right) L_{t-1} \right), 0 \right) \quad (5)$$

where L_{t-1} is the number of livestock from the previous year, K_L is the capacity (# livestock) given by

$$K_L = \frac{G_{yield,t}}{\eta_L^f (1 - \eta_L^r)} \quad (6)$$

where G_{yield} is the grass yield (kg) described by Eq. 4, η_L^f (kg/livestock/year) is the feed requirement rate per animal

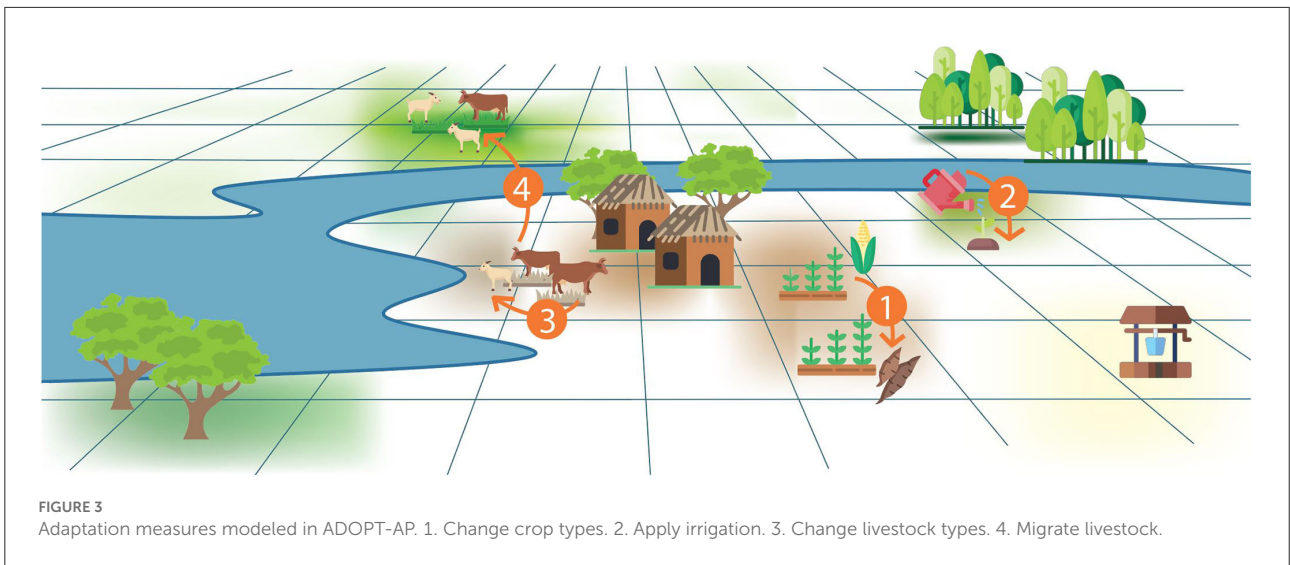


FIGURE 3 Adaptation measures modeled in ADOPT-AP. 1. Change crop types. 2. Apply irrigation. 3. Change livestock types. 4. Migrate livestock.

TABLE 1 Adaptation measure description, effect on environment and decision timing.

Nr.	Type	Adaptation measure	Description	Duration	Timing
1	Crop	Change crop types	Plant drought resilient crops (cassava instead of maize). Affects crop characteristics $a, b, p0, p1$ (Eq. 2); set crop type in that cell which affects K_e factors (actual evaporation), affecting yield of crop.	1 year	Begin October (start rainy season)
2	Crop	Apply irrigation	Apply irrigation over crop season. Abstract water from groundwater well or river and apply as additional artificial rainfall on soil. Affects yield and water demand.	10 years	Begin October (start rainy season)
3	Livestock	Change livestock types	Change from cows to goats. Affects livestock characteristics (lower water requirement, less fodder needed η_L^f , higher weight gain η_L^w , and growth rate r_{net}); effect on grass availability and water demand.	10 years	End May (start dry season)
4	Livestock	Migrate livestock	Migrate herd to other location. Affects grass availability (by eating of grass) and water demand spatially.	1 year	End May (start dry season)

and η_L^f is the feed residue rate (only 70% of unit feed is fit for livestock; Falvey, 1999). The growth rate r_L is a combination of the net birth rate r_{net} and the growth in livestock size as a result of the conversion of consumed grass to weight gain:

$$r_L = r_{net} + \max\left(\eta_L^w \left(\frac{G_{yield}}{(1 - \eta_L^f)L_t}\right), 0\right) \quad (7)$$

where η_L^w is the weight gain conversion rate (livestock/kg) and L_t the total number of animals in the grid cell. When a cell contains multiple livestock herds, the yield is proportionally distributed to the quantity of livestock in each herd.

2.4. Human decision-making

In the human decision-making component, agropastoralists can implement four adaptation measures (Figure 3, Table 1). Each implemented adaptation measure affects socio-hydrological interactions and the environment. Table 1 reveals which parameters are changed due to what measure. Two measures are short-term measures with a lifespan of 1 year (crop types and migrating). The other two measures have a lifespan of 10 years.

Each year, agents decide whether to adopt an adaptation measure. Crop-related adaptation measures are decided at the

beginning of October, the start of the long (main) rainy season. Livestock-related decisions are made at the end of May, before the long dry season. The *IntentionToAdapt_{t,m}* is the final variable that determines whether an agent will implement a specific measure; it is compared with a probabilistic threshold based on the measure's lifespan (Eq. S.1 in [Supplementary material](#)).

Agents receive and spend income each year after the long rainy season. Income is determined by the crop and milk production remaining after consumption, which is based on household size. In addition, agents have yearly expenditures depending on their herd and/or farm size. Their wealth and the potential impact of drought influence their adaptive behavior in the subsequent steps. See section process overview and scheduling in the [Supplementary material](#) for more details.

We applied the behavioral theory Protection Motivation Theory (PMT) (Eq. 8) to simulate whether an agent implements an adaptation measure (*m*) ([Maddux and Rogers, 1983](#)), which was successfully applied by [Wens et al. \(2020, 2021, 2022\)](#) in a case study in Kenya.

$$\text{IntentionToAdapt}_{t,m} = \alpha \cdot \text{RiskAppraisal}_t + \beta \cdot \text{CopingAppraisal}_{t,m} \quad (8)$$

where α [0.334;0.666] and β [0.334;0.666] are weights that sum up to 1 and are randomly determined following [Wens et al. \(2020\)](#).

PMT was created to understand adaptive human behavior (*IntentionToAdapt_{t,m}*, Eq. 8) under threat. It is based on two psychological factors: (1) *RiskAppraisals_t* (Eq. 9), which describes how individuals assess the severity of a threat (in this paper, the drought hazard) and (2) *CopingAppraisal_t* (Eq. 11), which describes how people assess ways they can react to the threat. The two cognitive components and their underlying perceptions are influenced by the agent's unique characteristics (age, gender, educational level, access to information, network, etc.). These characteristics are stochastically determined based on survey data from [Wens et al. \(2020\)](#).

Households' risk perceptions play an essential role in adaptive decision-making ([Grothmann and Patt, 2005](#); [Van Duinen et al., 2015](#)). Risk appraisal includes its perceived probability and severity ([Deressa et al., 2009, 2011](#); [Van Duinen et al., 2015](#)). It is partly based on the accumulative nature of past experiences, considered an individual drought memory ([Viglione et al., 2014](#)). Studies have also found that risk appraisal is primarily shaped by recent harmful events ([Gbetibouo, 2009](#); [Rao et al., 2011](#)). However, this awareness decreases over time ([Di Baldassarre et al., 2018](#)). Therefore, risk appraisal increases in relation to the relative damage experienced due to drought but decreases if no drought damage occurs. It is expressed as follows:

$$\text{RiskAppraisal}_t = \text{RiskAppraisal}_{t-1} + (\text{Drought} \cdot \text{DroughtDamage}) - 0.125 \cdot \text{RiskAppraisal}_{t-1} \quad (9)$$

where *RiskAppraisal_t* is initialized as a random value between zero and one [0;1], and the memory is the risk appraisal of the previous time step *t-1*. *DroughtDamage* is computed as the relative loss in livestock or crop production in a specific year compared to the average production of the previous 10 years ([Di Baldassarre et al., 2013](#)). It is only calculated when the Standardized Precipitation Evaporation Index ([Vicente-Serrano et al., 2010](#)) within a 3 months accumulation period (SPEI-3) falls below -1 at the decision moment. SPEI is computed for each grid cell individually, implying that the values can be different for every agent. *DroughtDamage* is calculated as follows:

$$\text{DroughtDamage} = 1 - e^{-\text{loss}} \quad (10)$$

Experiencing a risk does not result in adaptation; the perceived ability to act upon the risk also influences the decision-making process ([Deressa et al., 2009, 2011](#); [Eiser et al., 2012](#); [Gebrehiwot and Van Der Veen, 2015](#)). People should feel capable of dealing with the risk at hand (self-efficacy) ([Lalani et al., 2016](#); [Zhang and Dallimer, 2016](#)). Intrinsic factors in a household, such as education level, household size, age, network and gender, influence self-efficacy ([Mandleni and Anim, 2011](#); [Gebrehiwot and Van Der Veen, 2013](#); [Shikuku et al., 2017](#)). Households also have to believe they can pay for the costs (adaptation costs, i.e., the relative cost of the adaptation measure compared to the agent's liquidity) ([Van Duinen et al., 2015](#)). Finally, the perceived degree to which the adaptation options are likely to have an effect (adaptation efficacy) is also significant. The *CopingAppraisal_t* is thus a combination of the perception of self-efficacy, adaptation efficacy and the perceived adaptation costs of the agent:

$$\text{CopingAppraisal}_t = \gamma \cdot \text{SelfEfficacy} + \delta \cdot \text{AdaptationEfficacy} + \varepsilon \cdot \text{AdaptationCosts} \quad (11)$$

Receiving information (e.g., through farmer field schools or extension services) about how well an adaptation measure performs influences the perceived adaptation efficacy. The latter is determined by how much the livestock or crop production would have improved if the adaptation measure had been implemented:

1. *Change crop type*: crop-specific parameters (*a*, *b*, *P₀* and *P₁*) in Eq. 2 changed from maize to casava, resulting in different crop yields.
2. *Apply irrigation*: ratio AET/PET set to 1 in Eq. 2, resulting in different crop yields.
3. *Change Livestock types*: livestock-specific characteristics (Eqs. 5–7) changed to parameters for goats, resulting in different livestock production.
4. *Migration livestock*: gives maximum grass yield (Eq. 4) in surrounding cells, resulting in different livestock production.

If an agent does not have access to external adaptation information, they learn from what happens in their neighbors' field or within their neighbors' herd. Neighbors are the agents in neighboring cells and depend on the neighborhood radius in the model settings (8-connected if radius = 1).

2.5. Model setting and parameterization

Table 2 presents an overview of the data used for input in ADOPT-AP. The model simulation period is from 2005 to 2015. Section details of the Supplementary material provides an overview of the parameter settings used in the model framework.

2.6. Sensitivity analysis

To better understand the dynamic interactions in human behavioral responses to drought over time, we analyzed both

sides of the drought-human interaction and conducted a sensitivity analysis.

During the *sensitivity analysis*, we conducted a systematic Global Sensitivity Analysis (GSA; Sobol, 2001; Xu et al., 2004). Unlike the One-Factor-at-The-Time (OFAT) procedure, GSA tests the individual and combined effects of changing parameter values (Saltelli, 2002; Saltelli et al., 2010). Multiple Monte Carlo simulation runs were executed and evaluated for each parameter value combination since the model contains stochastic elements (Ligmann-Zielinska et al., 2014).

We varied the parameter values of the socio-hydrological interactions and human behavior components (Table 3). The parameters for socio-hydrological interactions are the distribution of the groundwater abstraction points (DA) (the likelihood of an abstraction point in a grid cell) and the irrigation demand factor (IF) of the soil moisture deficit (SMD), which defines irrigation demand (Section 2.3). For the human behavior component, α (AL) (Eq. 8) is considered (and thus β as they add up to 1) with the cost of adaptation measures (AM) (Section 2.4). The neighborhood radius (NR), indicating

TABLE 2 Data input for the different components of the ADOPT-AP model.

	Type	Variable	Source
Environment	Topography	Digital elevation model, river network	SRTM 1 Arc-second global map
	Meteorological	Precipitation, Evapotranspiration	MSWEAP ERA5-Land
	Soil	Soil texture Hydraulic properties	ISRIC, 2022
Socio-hydrological interactions	Crop land	Crop stages, crop season, max crop yield	Siebert and Döll, 2010
		Crop lands	MODIS
	Livestock	Water demand, feed requirements, weight gain rate, net growth rate, feed residue rate, milk meat production, max grass yield Grass lands	Otte and Chilonda, 2002 Siebert and Döll, 2010 MODIS
	Domestic water demand	Domestic water withdrawal per capita	Oageng and Mmopelwa, 2014
Human decision-making	Household characteristics	Age, household size, years of education, gender etc.	Wens et al., 2020
	Density	Population density grid	CIESIN, 2022

TABLE 3 Parameters and output variables in global sensitivity analysis.

Component	Parameters	Symbol	Unit	Values	Output
Environment	–				Mean Soil moisture, Discharge and Groundwater drought
Socio-hydrological interactions	- Distribution abstraction points	DA		[0.1, 0.9]	Mean livestock and crop production
	- Irrigation factor SMD	IF		[0.1, 2]	
	- Neighborhood radius	NR	Km	[1, 10]	
Human-behavior	- α alpha (risk appraisal)	AL		[0.33, 0.66]	Mean number of measures adopted
	- Costs measures	CM	\$	[20, 1,000]	
	- Neighborhood radius	NR	km	[1, 10]	

\$ refers to US dollars.

the circle of notion, is present in both components. The radius represents how far an agent can look for water or communicate with neighbors.

The effect of changing parameters is tested by examining how they affect output variables over the entire simulation period. Output variables related to the environment and human behavior components are considered. Hydrological variables relate to different types of drought: precipitation (meteorological drought), soil moisture (soil moisture drought), and discharge and groundwater level (hydrological drought). The different types of drought indicators (precipitation, soil moisture, discharge and groundwater deficit) are based on the 80th percentile threshold of the natural model run without human adaptation (Van Loon et al., 2022). Additionally, this threshold can be used to compare drought events between natural model runs (no influence from agents) and model runs including agents (affecting the environment). Hence, we can analyse the influence of agents on different types of drought.

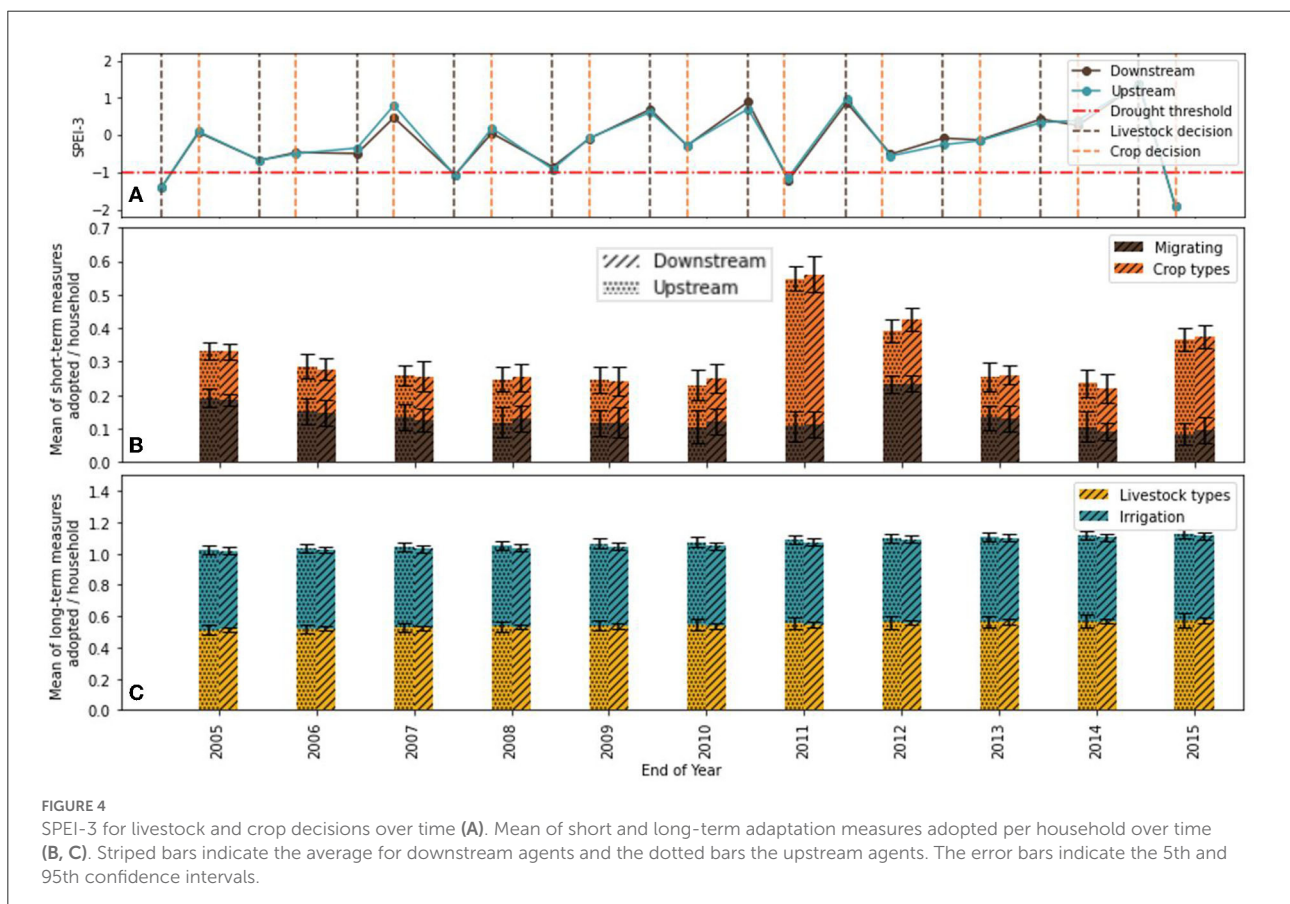
To summarize, the sensitivity analysis includes the following output variables: (1) *Environment*, mean soil moisture, discharge and groundwater drought; (2) *Socio-hydrological interactions*, mean livestock and crop production; and (3) *Human-behavior*, average adaptation measures adopted per household (see Table 3).

The GSA procedure is as follows: parameter sets per sample ($n = 12$) are produced following the Saltelli and SALib python package. The method requires 2^N distinct samples, depending on the number of parameters evaluated ($N = 5$), resulting in 32 distinct samples. Ten Monte Carlo simulations were run for all the samples, giving a total of $(12 \cdot 32 \cdot 10 =)$ 3,840 runs to evaluate the effect of changing parameter values.

A parameter's sensitivity is represented by the Sensitivity Index (SI):

- *First-order sensitivity*: The first-order SI measures a single parameter's contribution to the output variance.
- *Second-order sensitivity*: The second-order SI shows the interactions between two parameters.
- *Total-order sensitivity*: The total-order SI indicates the parameter's total contribution to the output variance, including first and higher-order interactions. The higher the index, the more sensitive the output variance is to changes in the parameter value (Saltelli et al., 2010).

A high sensitivity index reflects that variations in the parameter results into large variations in the output. The sum of first-order SI cannot exceed 1, but the total-order SI can.



3. Results

3.1. Agents' response to drought

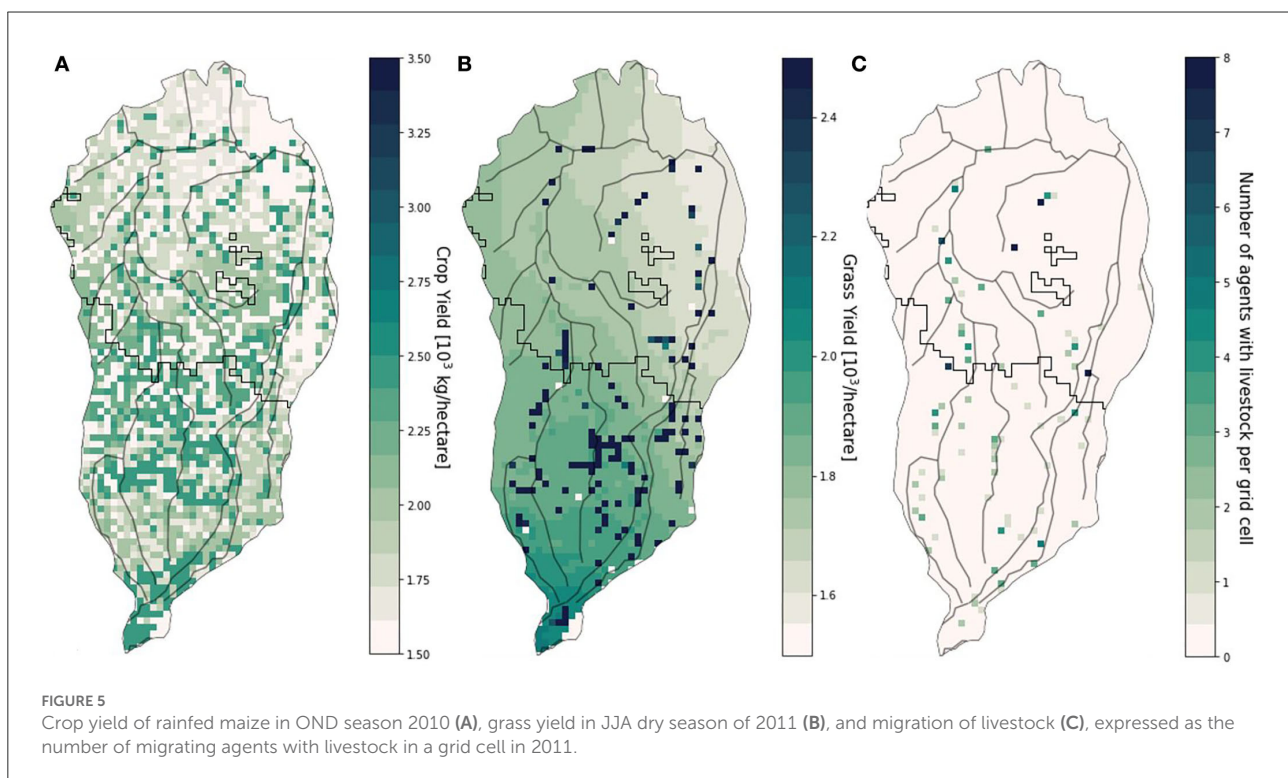
In this section, we examine the model simulations to explore how different agents respond to drought. Agents are divided into up- and downstream, based on their geographical location (see Figure 2). The results presented in Figure 4 indicate the average of multiple runs ($n = 10$) with the standard parameter settings (see section details in the Supplementary material) to better understand the dynamic interactions within human behavioral responses to drought over time.

Figure 4A indicates the experienced drought by upstream and downstream agents, expressed in SPEI-3 values, averaged over all agents in a group. Values below the red horizontal line (drought threshold: $< \text{SPEI-3}$ of -1) indicate drought events. The moment livestock decisions are made are represented with vertical brown dotted lines, with the years 2005 and 2008 being drought events (all lying below the SPEI-3 threshold of -1). At the timing of crop decisions, only the years 2011 and 2015 being drought events.

Figures 4B, C highlight the adoption of respectively long-term and short-term livestock and crop adaptation measures over time. The figure demonstrates that a drought event triggers a high implementation rate of short-term adaptation measures (Figure 4B). Conversely, when no (consecutive) drought events occur, the average adaptation rate of short-term measures decreases. High uptake of short-term adaptation measures can

be observed during and after 2011, which is known as one of the most severe droughts in the East Africa. The 2010/11 East Africa drought started in 2010 with a failed rainy season in October, November, December (OND season) and lasted until late 2011, with impacts felt until 2012 (Lott et al., 2013). It is observed that after the drought in the 2010 OND rainy season, the adoption of different crop types (Figure 4B) increases for the both upstream and downstream agents (~ 0.6 measures per agent). After the June, July, August (JJA) dry season in 2011 an increase in the uptake of migration as short-term adaptation measure is observed.

An explanation for the difference between up and downstream agents is that, although all agents have an elevated drought risk perception during and after a drought event, the risk perception is different between upstream and downstream agents due to a differentiated experience with drought impacts. The risk appraisal for the downstream communities in 2011 for crop decisions and in 2012 for livestock decisions was higher (~ 0.93 for crops and ~ 0.36 for livestock, respectively) than that of the upstream communities (~ 0.88 for crops and ~ 0.30 for livestock, respectively) due to greater drought damage. Combined with a higher coping appraisal, this results in higher uptake of short-term adaptation measures. Due to the differences in risk appraisal for crops and livestock, the uptake of short-term measures was higher for crop decisions in 2011 (~ 0.5 of changing crop types), than for livestock decisions in 2012 (~ 0.25 of migration).



There are no major changes in long-term adaptation measures (livestock types and irrigation) over time: a household has, on average, 0.5 long-term adaptation measures (due to initialization, Figure 4C). However, there is a steady but slight increase (~0.1 measures per agent) in the uptake of long-term measures. In contrast to short-term measures, upstream agents adopt more long-term measures than downstream agents, particularly irrigation. An explanation could be that because the upstream agents have more assets compared to downstream agents (average 25% more) due to more favorable climatic conditions, they more likely to adopt a costly long-term measure.

3.2. Socio-hydrological interactions

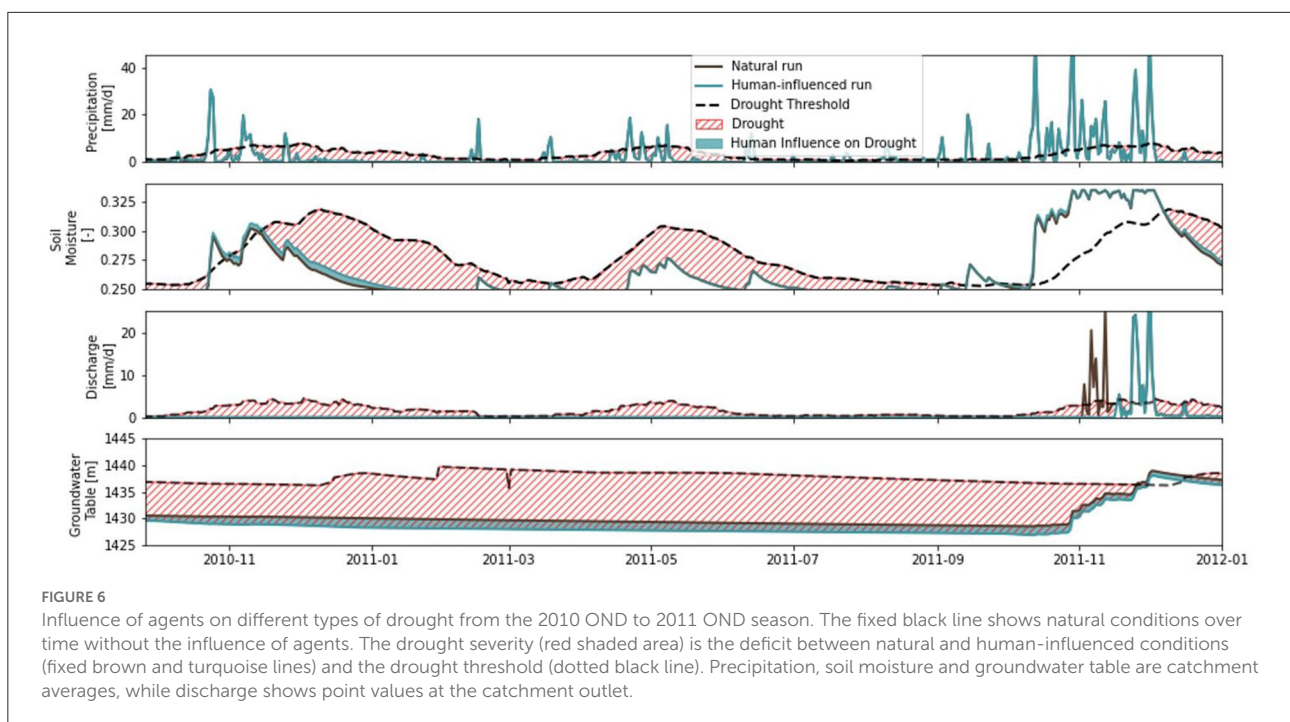
In Figure 5 various variables within the *socio-hydrological interactions* component are presented. The variables are outcomes of a single example run. Figure 5A shows the crop yield when the agents would have rainfed maize. Upstream agents (i.e., agents in the south) have a higher potential crop yield compared to downstream agents. On average, the crop yield for upstream agents is 1.98 tons/hectare and for downstream agents 1.7 tons/hectare. The grass yield for the JJA dry season in 2011 is, similarly to the crop yield, higher for upstream agents (~1.70 tons/hectare) compared to downstream agents (~1.63 tons/hectare). Some areas with very high grass yields are observed near the rivers. Figure 5C indicates the livestock migration in 2011, expressed as the number of agents

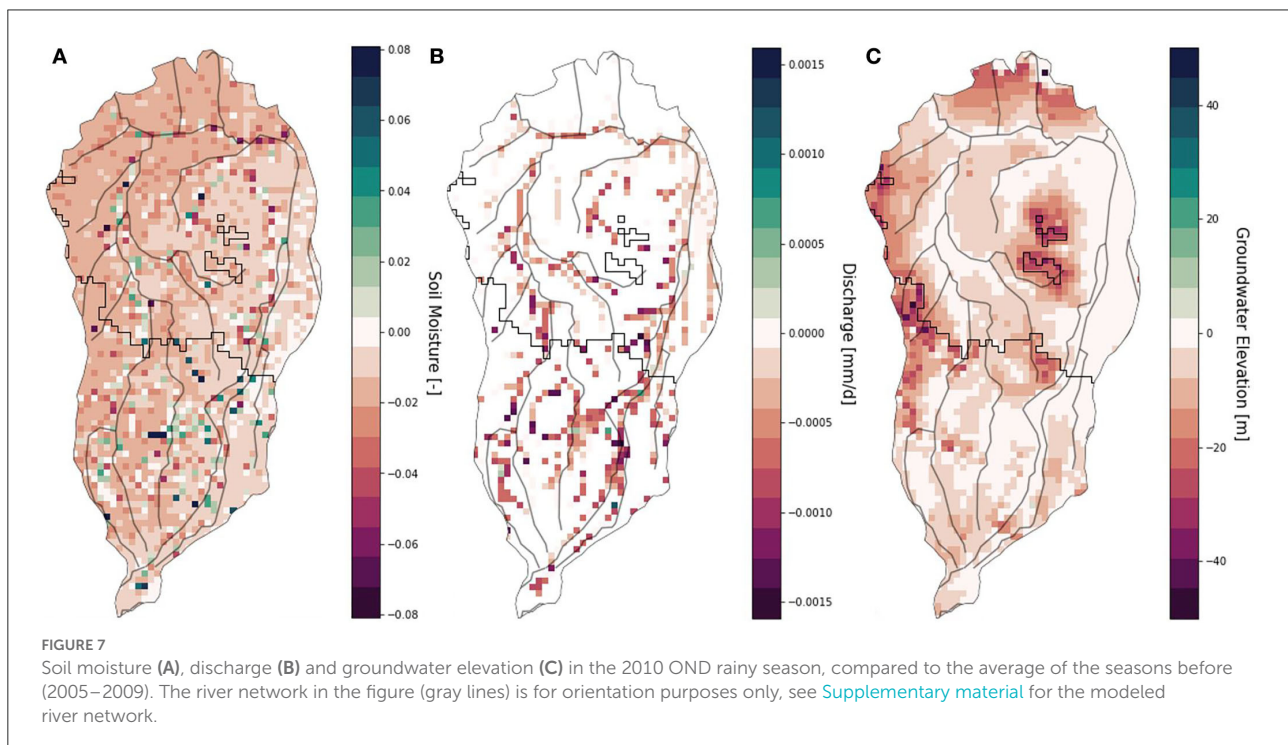
that have moved with their livestock to a specific grid cell. It can be observed that especially the areas around the river streams have an increased number of agents with their livestock, which indicates that in the model the drought has forced pastoralists to search for areas with higher grass production, such as near the rivers (as observed in Figure 5B).

3.3. Drought response to agents

Figure 6 demonstrates the effect of human adaptive behavior on drought propagation in the OND season in 2010 (start of the 2011 East African drought). Four time series of drought indicators are represented: the 80th percentile values of precipitation, soil moisture and the groundwater table averaged for the catchment, and discharge at the outlet (see Section 2.6). We distinguish natural conditions, indicating model runs without the influence of human agents (fixed brown line) and conditions influenced by the agents' adaptation decisions in the ADOPT-AP model (turquoise color). The drought severity (red shaded area) can then be defined as the deficit between natural (fixed brown line) or human-influenced (fixed turquoise line) conditions and the drought threshold (dotted black line). Finally, the turquoise band indicates the human influence on different types of drought.

For all three hydrological variables, the influence of human adaptive behavior is evident. Average soil moisture increases under human influence through irrigation by farmers,





resulting in a decrease in soil moisture drought. Conversely, agents decrease the groundwater table elevation through domestic and irrigation water use, increasing hydrological drought. For discharge there is no change in the period from the 2010 OND season until the 2011 OND season because in both scenarios the discharge is zero due to the drought. The drought event ends in the 2011 OND season, causing the discharge to rise early and end of November in the natural scenario. However, the first discharge peaks are not present in the human-influenced scenario and only after continued rain the river in the human-influenced scenario starts to flow, indicating the effect of human water abstractions.

The spatial variability of (human-influenced) soil moisture, discharge and groundwater levels of the 2010 OND season compared to the average of the seasons before, is plotted in [Figure 7](#). Soil moisture is decreased throughout the catchment, with a higher decrease for the western side of the catchment compared to the eastern side. There are some cells that have an increase of soil moisture even during the drought because of irrigation practices. Discharge is also decreased compared to the previous seasons, with the most extreme low flows seen in the upstream part of the catchment. Groundwater levels are decreased throughout the catchment, especially in the western part of the catchment, similarly to the soil moisture plot. The decreases of river discharge and groundwater level are due to the combination of drought and increased abstraction for irrigation.

3.4. Sensitivity analysis

[Figure 8](#) illustrates the results of the sensitivity analysis: the sensitivity of drought, production and adaptation output variables to different model parametrisation assumptions. Rows represent the different modeling output variables. The top three rows show the drought-related output variables (soil moisture, discharge and groundwater table). The middle rows represent livestock and crop production, and the bottom four rows show the results for the four adaptation measures (migration, irrigation, crop and livestock types). The columns represent the model variables that were varied during the sensitivity analysis runs (see [Section 2.5](#), [Table 3](#)).

3.4.1. Drought variables

The different types of drought are primarily influenced (indirectly) by the irrigation demand factor (IF), as this factor determines the amount of water abstraction for irrigation purposes from groundwater and rivers, and therefore also the amount of irrigation added to soil moisture. Soil moisture and discharge drought are not sensitive to first-order or second-order interactions, indicating that more complex interaction are important in determining these types of drought. Groundwater drought is, in addition to IF, sensitive to alpha (AL) and the neighborhood radius (NR). These patterns are similar to that of migration and changing livestock types, giving an

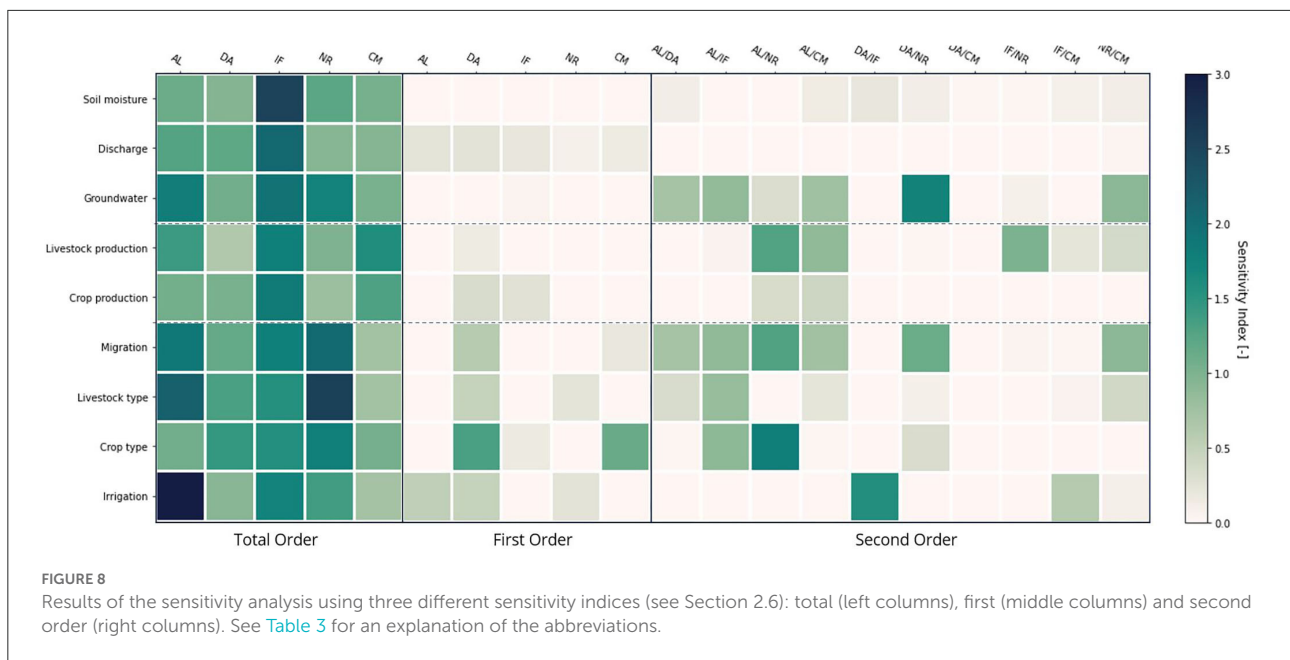


FIGURE 8 Results of the sensitivity analysis using three different sensitivity indices (see Section 2.6): total (left columns), first (middle columns) and second order (right columns). See Table 3 for an explanation of the abbreviations.

indication that migration and livestock types influence the groundwater drought. For example, if many agents come together to one grid cell, the livestock production decreases due to less available grass per agent, and consequently water demand also decreases. Similarly, changing crop types decreases water demand as well, as goats require less water than cows. However, as goats also require less grass, the production might increase (compared to cows) and the water demand increases again. Second-order interactions show that the interactions between distribution of abstraction points (DA) and the neighborhood radius are of high importance. A larger neighborhood radius increases the area where agents can take water and interact with other agents. The combination of agents having a larger (or smaller) area to look for potential water sources (NR) and a higher (or lower) chance of having a groundwater abstraction points (DA) influences the groundwater drought.

3.4.2. Livestock and crop production

Livestock production is highly sensitive to three parameters. The irrigation demand factor (IF) influences water availability (as found in previous section), which in turn influences grass availability and livestock production. In addition, alpha (AL) and the cost of measure (CM) influence the livestock production. This finding suggests that adaptation behavior plays a significant role in determining livestock production. In addition to the second-order interaction between IF and NR, the NR interacts with the AL in determining livestock production, while AL interacts with CM as well. NR, AL and CM

all three influence the Coping Appraisal, which confirms that adaptation behavior is essential for livestock production. Crop production is primarily influenced by the IF, as crop production and irrigation are strongly linked (irrigation increases crop production). DA and IF have a small direct influence on crop production; a higher chance of being near a water source and an increased irrigation demand increase crop production (and *vice versa*).

3.4.3. Adaptation measures

The uptake of migration as a short-term measures is mostly influenced by AL, IF, and NR. This finding indicates that the uptake is both influenced by water availability (through IF and NR) and adaptation behavior (AL and NR). Especially the interactions between NR and other parameters (AL, DA, CM) contribute to the high total SI. The neighborhood radius (NR) is the most important parameter is determining whether an agent will migrate. This can be explained by the fact that NR determines how far an agent can migrate and can look for better grass conditions in the area. Similarly to migration, the uptake of livestock types is largely influenced by AL and NR. This finding can indicate that coping appraisal is important, as the weighting (compared to risk appraisal) is determined by AL and NR determines the self-efficacy and adaptation efficacy (knowledge of measure in neighborhood). The adoption of changing crop types is most sensitive to DA, IF, and NR, indicating that water availability may drive the adoption. DA and CM have a direct influence, while AL in combination with IF and NR have an indirect influence.

Irrigation uptake is highly sensitive to the AL and IF. AL determines the relative weighting of coping appraisal vs. risk appraisal, implying that one factor is more important than the other for adopting an irrigation measure. IF influences the adaptation efficacy (through increased crop production) of the irrigation measure. The second-order interactions show that especially the interactions between DA and IF are important; IF only comes into play when there is also a water source to abstract water from.

4. Discussion and recommendations

The drought adaptation modeling framework ADOPT-AP was developed to capture dynamic feedback between heterogeneous behavior and drought risk concerning agropastoral livelihood decisions in dryland regions. However, aspects of the framework generate uncertainty in simulated results and require further attention in future research. In this section, the uncertainty of the modeling framework is discussed, together with recommendations for developing the model and a reflection into unintended consequences emerging from feedbacks and coevolution of human-water systems.

4.1. Sensitivity of modeling framework

In general, the modeling framework produced results that confirm the findings of earlier studies. Our results clearly demonstrate that drought events affect risk perception. Depending on the perceived coping capacity, the level of adaptation increases during and after a drought. The results also indicate that each household adopts, on average, 0.1–0.2 short-term measures during a simulation period of 10 years. These figures are similar to the adoption of mulch and *fanya juu* terraces described in Wens et al. (2020): 0.08–0.25 measures. Regarding long-term measures, the numbers in this study, averaging ~ 0.05 additional adaptation measures per household after initialization, are comparable with Wens et al.'s (2020) results: a maximum of 0.025–0.5 measures per household (well and drip irrigation). A novel finding in this study is the differentiation in the hydrological environment due to the ABM's bi-directional coupling to a hydrological model. For example, differences were observed between upstream and downstream communities, indicating a drought influence that varies across the catchment area (downstream communities were the most severely affected and adopted more short-term measures).

The sensitivity results show that the amount of irrigation water used (IF) influences all output variables analyzed; drought, livelihood production and adaptation decisions. It highlights the importance of water-human feedbacks in assessing drought risk. Besides, as we do not precisely know the appropriate

irrigation demand factor (IF), it is of key importance that empirical research should further investigate this. In addition, the sensitivity analysis shows that the total-order SI cannot be fully explained by the first- and second-order SI, indicating the complexity of the model which is driven by many higher-order interactions.

4.2. Recommendations for future drought adaptation modeling

Our model does not capture all the factors driving the adaptive behavior of pastoralists to droughts. An essential next step in the model's development is to use empirical data from households in the specific region to calibrate behavioral theories and socio-hydrological interactions. This step is significant because the sensitivity analysis indicates the modeling outcomes' sensitivity to behavioral parameters such as the influence of neighbors, risk perception of drought events and perceived coping capacity, as well as socio-hydrological parameters such as the distance to wells and water use for irrigation.

Furthermore, several behavioral components can be influenced by external drivers (e.g., war, dynamic market prices related to crops and livestock and diseases), which could subsequently be included as additional modules. For example, since household assets (e.g., crop and milk sales) largely depend on fluctuating market prices, an economic model could be implemented to simulate such influences (Schreinemachers and Berger, 2011; Amaya et al., 2021). In addition, the influence of government policies and campaigns on the uptake of adaptation measures by pastoralists could be added. For example, Wens et al. (2022) demonstrate how extension services and providing drought risk information to farmers in Eastern Africa influence risk perception and adaptation. Finally, instead of using SPEI as a drought risk indicator influencing the risk appraisal of PMT, different perceptions of drought could be incorporated, including current or recent hydrological conditions, local knowledge of drought predictions or forecast information. Adaptation is currently limited to four measures, but could be expanded in a new version of the model. For example, an adaptation measure that changes water availability at the household level (e.g., rainwater harvesting) would be interesting to study as it can change drought propagation over time (Lasage and Verburg, 2015). In future studies, it is recommended to verify whether practices such as buying and selling livestock are important in the region and whether they should be incorporated as an adaptation measure in ADOPT-AP.

As the agents are heterogenous with different characteristics and responses, the differences in income from livestock and crop production can differ substantially. Further analysis is recommended on factors (initial assets, livestock size, area of

land, etc.) that drive inequitable income distributions (Alam et al., 2022).

Additional agents could be added to ADOPT-AP. For example, government institutions at different organizational levels could be included to facilitate policy (efficiency and enforcement) analysis. Other agents, such as large-scale farms or private company water users, allow for an assessment of the effect of these actors on overall water availability (Kaiser et al., 2020). Climate scenarios or storylines could be explored to understand how future water–human interactions are shaped and influence drought impacts.

More research is also needed on the hydrological aspects and how adaptation decisions are processed in the DRYP model. For example, complex land-surface interactions within the DRYP 2.0 hydrological model would allow assessments of adaptation measures that alter water storage through vegetation (e.g., agroforestry) (Wallace et al., 1999).

4.3. Implications and unintended negative outcomes of adaptation

In a changing climate, it is crucial to develop adaptation measures to sustain livelihoods and ecosystems (Pörtner et al., 2022). Most studies focus on the positive sides of adaptation, and how drought adaptation (e.g., irrigation) reduces drought risk. However, this research shows there can be negative unintended consequences from implementing drought adaptation measures that can emerge from the coevolution between water and human systems (Di Baldassarre et al., 2018; Ward et al., 2020). Alam et al. (2022) categorizes these unintended consequences into negative hydrological externalities and unexpected social feedbacks.

ADOPT-AP is capable of capturing these feedbacks in a spatially explicit manner, as it captures both hydrologic processes and heterogeneity of people. An observed example of an unintended hydrological consequence is that irrigation of crops can lead to a reduction of streamflow or a lower groundwater table, affecting communities downstream more severely. This effect is known as the downstream effect of reservoir development, and our spatial modeling framework shows that upstream water- and land users may decrease the streamflow for downstream users, both directly through abstraction (including groundwater) and indirectly through land changes. Groundwater- and surface water abstractions directly lead to a reduction in downstream (groundwater-) flow thus less water availability for downstream users. Similarly, changes in upstream land use may increase evapotranspiration, decrease runoff, and thus decrease downstream water availability (Veldkamp et al., 2017).

We performed a test that compares the water availability of downstream users (1) with upstream users and (2) without upstream users. The simulation shows that adding upstream users causes a decrease of around 1% in soil moisture, around 1 meter of decrease in groundwater level, and 5% decrease in discharge, compared to the situation without upstream agents.

Another unexpected societal feedback is related to the changes in water demand due to increased irrigation practices and changing livestock types. When comparing a model run with all agents adapting to a run with all agents not adapting, there is an increase of irrigation water demand of around ~15%, while crop production is increased by 3.5%. However, while pastoralists try to adapt to drought in the adaptation scenario to lower the risk for livestock, there is indeed a decrease of livestock water abstraction by ~2% compared to no adaptation, but livestock production is decreased by 2%. This can be explained by the way migration is currently modeled; multiple agents to come together in one grid cell, causing a decrease of grass availability and thus livestock production (and water demand) per agent.

The phenomena of multiple agents migrating to a single grid cell is observed in Figure 5C, and shows the emerging pattern of agents migrating with their livestock toward the rivers. Some case studies indeed show that pastoralist move to flood plains of the rivers in times of drought (Mulder, 2019).

5. Conclusion

The ADOPT-AP modeling framework focuses on improving drought risk assessments by including the dynamic feedback between the hydrological system and the adaptation behavior of a heterogeneous population under drought risk. We coupled a spatially distributed hydrological model to a human behavior-centered agent-based model to simulate feedbacks among communities and between people and their environment. These feedbacks were simulated directly through communication structures and indirectly *via* water and land use management. Understanding these two-way feedbacks between farmer adaptation and the hydrological system helps to improve future drought impact estimates and allows possible drought policies and their implementation to be tested.

Our results indicate that farmers respond differently to drought due to differences in their hydrological environment. In our case study region, downstream communities were impacted more heavily in the past; these communities implemented more short-term adaptation measures than upstream communities. While on the contrary, upstream agents implemented more long-term adaptation measures due to more favorable climatic conditions increasing their resources. We demonstrated how agents respond to drought events (production losses) and how this can lead to the uptake of different adaptation measures.

Furthermore, we evidenced how the uptake of these measures can influence different types of drought (soil moisture and hydrological drought), either increasing or decreasing the severity of drought events. Livestock and crop production are particularly sensitive to water availability (influenced by amount of water abstracted for irrigation).

ADOPT-AP is able to access the unintended negative outcomes of adaptation that can emerge due to the coevolution between water and human systems. Examples include the influence of upstream communities on the water availability of downstream communities and the changing water demand and production due to adaptation.

Further research could include additional empirical data (e.g., from surveys) to simulate more realistic human behavior in ABMs and add adaptation measures and feedback that focus on vegetation dynamics and water storage. Furthermore, different types of agents could be added to analyse the effect of (future) policy implementations. Climate scenarios could be explored to understand how future water–human interactions are shaped and influence drought impacts.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary material](#), and can be found at: <http://doi.org/10.5281/zenodo.7447665>. Further inquiries can be directed to the corresponding author.

Author contributions

IS: conceptualization, software, visualization, and writing—original draft. JB: conceptualization, software, and writing—review and editing. TH, AL, and JA: conceptualization, supervision, and writing—review and editing. EQ: software and

writing—review and editing. MW: methodology and writing—review and editing. KH: writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frwa.2022.1037971/full#supplementary-material>

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