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The effects of upstream water abstraction for commercial export farming on drought risk and impact of agropastoral communities in the drylands of Kenya

Ileen N. Streefkerk[1]*, Jeroen C.J.H. Aerts[1,2], Jens de Bruijn[1,3], Khalid Hassaballah[4], Rhoda Odongo[1], Teun Schrieks[1], Oliver Wasonga[5], and Anne F. Van Loon[1]

[1] Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, Netherlands
[2] Deltares, Delft, Netherlands
[3] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
[4] IGAD Climate Prediction and Applications Centre (ICPAC), Nairobi, Kenya
[5] University of Nairobi, Nairobi, Kenya

Correspondence to: Ileen. N. Streefkerk (ileen.streefkerk@vu.nl)

Abstract. In the Horn of Africa Drylands (HAD) conflict over water and vegetation is prominent. Additionally, large-scale land acquisitions (LSLAs) are increasing the competition of water, putting local communities at greater risk. A key impact of increasing LSLA's is the decrease in water and land availability for vulnerable agropastoral communities. Despite recent studies, there is still a lack of research that includes the influence of upstream-downstream dynamics on drought risk and impacts of agropastoralists. Therefore, this study further develops an agent-based model (ADOPT-AP) to investigate how upstream large scale commercial farms influence downstream drought risk and impact of agropastoralists in the Upper Ewaso Ng'iro catchment in Kenya. After the model has been calibrated and validated, we assess how commercial exporting farms affect drought risk and impact of downstream communities by simulating different scenarios where the farms are replaced by agropastoral communities or forests. Our results show how both drought hazard characteristics and impacts differ among these scenarios. The analysis shows that in the scenarios where these farms are replaced by forests or communities, drought conditions are alleviated by increasing soil moisture, streamflow, and groundwater tables. These improvements are linked to reduced water abstraction and increased infiltration, benefiting downstream communities by decreasing the distance to household water, and increasing crop and milk production in times of dry periods. Policy interventions should prioritize equitable water distribution, regulation of water use, and promotion of sustainable agricultural practices to mitigate long-term impacts on water resources and community resilience.

1 Introduction

Drought poses a thread in the already existing water challenges in the Horn of Africa Drylands (HAD) (Solomon et al., 2018,). Drought hazard and risk are, however, not merely a natural phenomenon driven by rainfall deficits and other hydrometeorological processes. Droughts are also shaped by human behaviour and interventions (Van Loon et al., 2016). For

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example, large-scale land acquisitions (LSLAs) for commercial farms that use large quantities of (ground-) water are further increasing the competition of water, putting local farmers and communities at increased risk to droughts (Chiarelli et al., 2022). These LSLA's may be in the form of large private ranches, industry, and commercial export farms (Mkutu & Mdee, 2020). A key impact of increasing LSLA's is the decrease in water and land availability for vulnerable agropastoral communities (Lanari et al., 2018). Agropastoralism is the main source of livelihood to millions of people in Kenya accounting for 10-44% GDP (Nyariki and Amwata, 2019). For such communities, drought adaptation is key to anticipate current- and future drought risk (Pörtner et al., 2022).

To support drought adaptation for agropastoralists, it is important to understand the factors that influence adaptation actions they can take themselves, and how these actions interact with large scale water users (such as commercial farms) and governmental policies (Alam et al., 2022; Reckien et al., 2023). There is an emerging literature that captures the factors driving drought risk management by agropastoral communities in Kenya and what policy interventions may stimulate drought adaptation. For example, Wens et al. (2021), show that mistrust in drought forecasting (-29%) serves as a barrier to adaptation, while experience with past adaptation decisions (+44%) stimulate the intention to adopt new drought adaptation measures. Streefkerk et al. (2023) found for a case study in Kenya that low levels of wealth and high distance to wells have a large effect on water availability. Furthermore, a recent study by Schrieks et al. (2023) shows that the likelihood that agropastoralists implement adaptation measures is positively influenced by, among other, the perceived efficacy of adaptation measures and confidence in their ability to adapt (perceived self-efficacy). Other factors influencing drought adaptation by agropastoralists are gender, education level, access to financial resources, and access to government support or aid.

Knowing the factors that influence local drought adaptation may support identifying (governmental policy) actions to increase the uptake of drought adaptation. For example, Wens et al. (2022) include ex-ante cash transfers and timely extension services. Less known are the effects of large-scale commercial farms on drought for agropastoralists and which policies may support risk reduction and the equitable distribution of water (e.g. Giger et al. 2022). Studies have shown that drought risk often increases downstream as water is stored and abstracted in upstream areas (Van Oel et al., 2018; Veldkamp et al., 2017). Water use by commercial horticulture farms may play a role in upstream – downstream water conflicts, and water use by large farms already exceeds minimum water availability in the dry season (Lanari et al., 2018). In the longer term, this may lower groundwater tables and increase drought risk in the entire region and for all water users (e.g. Castilla-Rho et al, 2015).

What is lacking in these studies, however, is a systematic assessment of these upstream-downstream interactions and an evaluation of drought adaptation options for agropastoralists being affected by upstream commercial farms (Kiteme et al., 2021). The main goal of this paper is, therefore, to develop a coupled hydrological and agent-based model (ADOPT-AP) to investigate the influence of upstream large scale commercial export farms on downstream drought risk and adaptation by agropastoralists. We apply and test the ADOPT-AP model for the Ewaso Ng'iro north catchment in Kenya. Main novelties of our method are the ability to capture heterogeneous and dynamic drought-human interactions (including different water users) in a spatially-explicit manner. After the model has been calibrated and validated, we test how commercial exporting farms affect drought risk and impact of downstream communities.

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2 Case Study Area

The Ewaso Ng'iro North catchment, spanning 210,000 km2 , sources its water primarily from Mount Kenya and the Aberdare Range (Kiteme et al., 2021). These main water towers, located to the south of the catchment, contribute to the varied climatic zones observed in the region (Fig. 1). The upstream areas exhibit a humid climate with an altitude up to 5000 m and mean annual rainfall of 1500 mm, transitioning to semi-arid and arid conditions downstream with a minimum altitude of 500 m and mean annual rainfall of 350 mm (Mungai et al., 2004). This climatic gradient is essential in determining land use and the livelihoods of the local population.

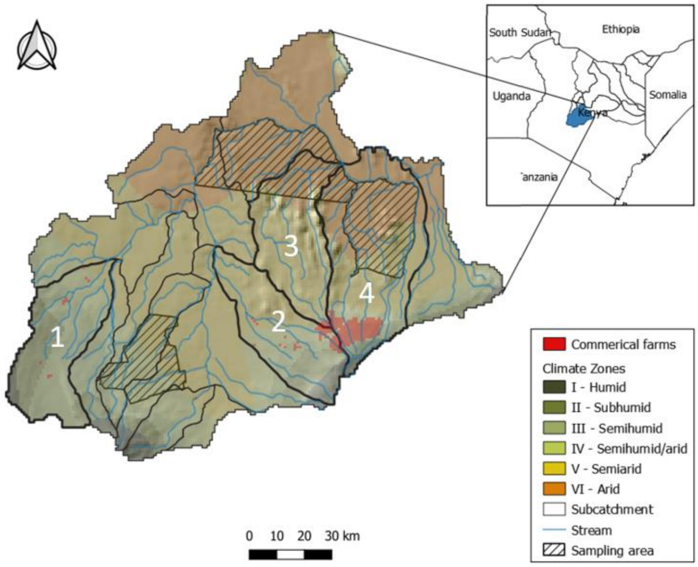

Figure 1: Study area: aridity zones (Gichuki et al., 2002), rivers, commercial export farms in the Upper Ewaso Ng'iro catchment.

The upstream regions, characterized by higher rainfall and more stable water supplies, are dominated by cropland and forests. This area supports large commercial export farms, particularly horticulture and floriculture, which benefit from the favourable year-round climate and abundant water resources (Lanari et al., 2018, Wiesmann et al. 2000). They are indicated in red south east of the catchment in Fig. 1. These farms are primarily concentrated in sub-catchments 1 and 2, with greenhouse operations spread throughout these areas. Sub-catchment 3 has similar conditions but only upstream, while sub-catchment 4 houses open farms, such as those cultivating wheat. Conversely, the downstream regions (sampling area), marked by arid conditions and covered in grassland and shrubs, support agropastoralism and pastoralism. Local livelihoods here are heavily dependent on livestock herding due to the scarce water resources. Schrieks et al. (2023) highlight in their survey of the local farmers and agropastoralists, that in the humid to semi-humid and semi-arid zones, crop farming and agropastoralism prevails, respectively. While in the arid zones, pastoralism is the dominant livelihood (Kiteme et al., 2021).

The expansion of commercial export farms has dual impacts: they create employment opportunities but also lead to conflicts over water resources with local agropastoral communities (Kiteme et al. 2021). The intensive water use by these farms, especially for irrigation in horticulture, has been shown to reduce streamflow by up to 32% (Lanari et al., 2018). This

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significant reduction in water availability exacerbates the challenges faced by local communities, who already struggle with limited water resources.

Water resource management in Kenya has evolved over the years. The Water Resources Authority (WRA) is responsible for regulating and managing water resources at a national level. However, the governance structure has been increasingly decentralized, promoting more local participation (Dell Angelo et al., 2016). The Water Resource Users Associations (WRUAs), established following the 2012 Water Act, play a critical role in local water management, including monitoring and enforcing water abstraction permits and implementing conservation programs (Baldwin et al., 2016). Despite these efforts, equitable water distribution remains a challenge (Lesrima et al., 2021).

The Ewaso Ng'iro North Development Authority is tasked with coordinating regional development initiatives within the basin, i.e., the case study area (Kiteme et al., 2021). Although the decentralized governance structure marks an improvement over the central governance model of the 2002 Water Act, disparities in water distribution persist, as noted by Dell Angelo et al. (2016).

3 Data and methods

Figure 2 briefly describes our approach by further developing the ADOPT-AP model (Streefkerk et al., 2023), which integrates (1) Hydrology: the DRYP hydrological model (Quichimbo et al., 2021) with (2) an agent-based decision model (ABM), which simulates adaptation decisions by agropastoralists. These two parts are connected through (3) Socio-hydrological interactions. These interactions are modelled as rules that describe the feedback between decision making and the hydrological system.

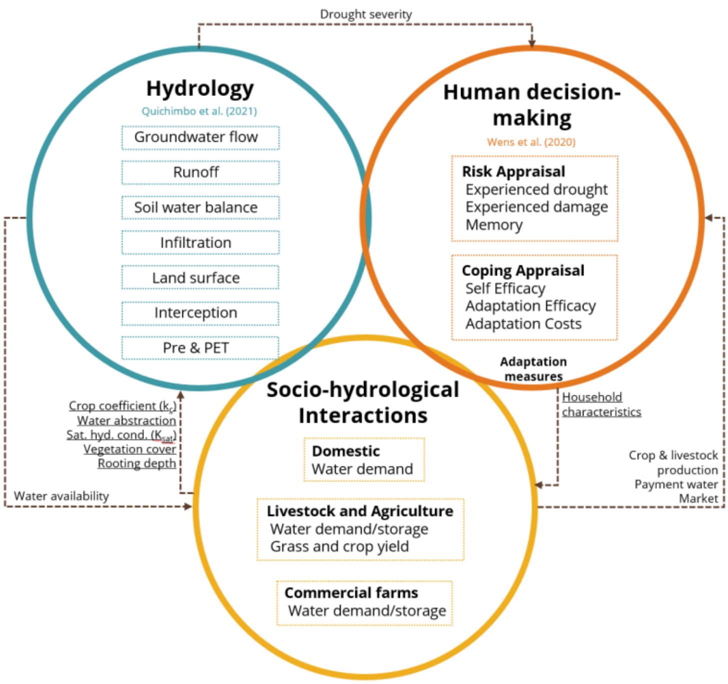

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Figure 2: ADOPT-AP modelling framework, consisting of three modules; hydrology, human decision-making, and socio-hydrological interactions.

This coupled model allows for assessing how the main water users ('agents') respond to drought. Agropastoralists grow crops and tend livestock to sustain their livelihood. They can take six adaptation measures to cope with droughts to meet their water demand and required grass/crop yields. Adaptation decisions by agropastoralists are made following the protection motivation theory (PMT), which is based on (a) the perceived threat of drought risk and (b) their perceived coping capacity to implement drought adaptation measures. The agropastoralists make adaptation decisions at yearly time steps. The model includes ~15000 agents with a heterogeneous set of characteristics (e.g. income, age, etc.) at a spatial resolution is 1x1 km^2. This means each grid cell has one agropastoralist agent, representing multiple households (depending on population density). In addition, commercial export farms are represented through water management rules defining the required storage and abstraction of water. We run the model for three scenarios and assess the effect of each scenario using drought and impact metrics.

3.1 Hydrology

DRYP is a process-based distributed hydrological model developed to simulate hydrological processes in dryland regions (Quichimbo et al., 2023). Precipitation and potential evapotranspiration are the main parameters where precipitation is divided into infiltration and surface runoff, depending on soil moisture conditions. Runoff is generated using a routing routine based on elevation. Groundwater is discharged into the streams as baseflow above a certain channel stream stage threshold value. Water from groundwater aquifers and surface streams can be abstracted by users. In addition, irrigation water can be applied to the land (modelled as additional rainfall). Human-induced land use changes are included by altering the crop coefficient (k_c), saturated hydrological conductivity (K_{sat}), vegetation cover, rooting depth, influencing hydrological processes such as interception, actual evaporation and infiltration. A more detailed description of the hydrological model can be found in Quichimbo et al. (2021, 2023).

Additional variables are added to the interception component of the hydrology component to enable simulating adaptation by individual agropastoralists and commercial farms. The monthly soil adjusted vegetation Index (SAVI) is obtained from Sentinel-2, and the fraction of vegetation cover is from Copernicus Global Land Service. The biome specific coefficient is taken from Kergoat (1998). Discharge is used for calibration and verification of the model and provided by the Centre of Training and Integrated research in ASAL Development (CETRAD).

3.2 Human decision-making

Following the Overview, Design Concepts and Details + Decisions (ODD+D) protocol (Müller et al., 2013), a detailed overview of the modelling structure and scheduling is given in Supplement S1. We here briefly summarize the main procedures.

Each year, agents decide whether to adopt an adaptation measure. They spend income on adaptation measures and the height of these expenditures is depending on their herd- and farm size. Income is determined by the crop and milk production

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remaining after consumption. Agropastoralists can take six drought adaptation measures (numbered 1-6 in Fig. 3). Four of these have been described by Streefkerk et al (2023): (1) change crop type, (2) apply irrigation, (3) Change livestock type, and (4) Migrate with livestock. In this paper we expand the model with two additional adaptation measures (Table 1): (5, Fig. 3) water harvesting and (6, Fig. 3) soil conservation techniques. These two additional measures have been selected as they are widely applied in the Isiolo area as described by Schrieks et al. (2023). Both have an influence on the environment (i.e. modify properties in the hydrological model when adopted) (see Table 2). Adaptation costs for the six measures are obtained from the World Overview of Conservation Approaches and Technologies (Kentainers, 2024; Keynaseed, 2024; WOCAT, 2024).

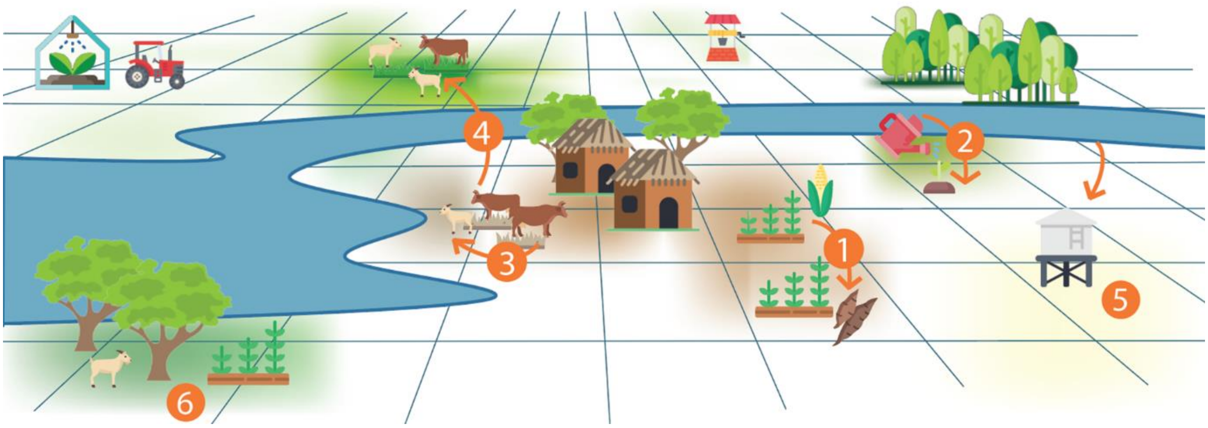

Figure 3: All adaptation measures implemented in the model. Adaptation measures water harvesting (5), and soil moistures conservation (6) are added compared to Streefkerk et al, (2023).

Table 1: Adaptation measures added to ADOPT-AP.

Adaptation measure	Description	Duration	Timing
Change crop type	Plant drought resilience crops (cassava instead of maize). This measure affects the crop yield (based on the ratio between actual and potential evapotranspiration).	1 year	Beginning of October (start rainy season)
Apply irrigation	Apply irrigation over crop season. Wat is abstracted from groundwater or river and is applied as additional rainfall on the soil in the DRYP model	20 years	Beginning of October (start rainy season)
Change livestock type	Change from cows to goats. With this change, less water and grass are needed. This has an effect on grass availability and water demand	20 years	End May (start dry season)
Migrate livestock	Migrate herd to other location. Affects grass availability and water demand	1 year	End May (start dry season)
Soil conservation	Soil conservation techniques such as agroforestry, half-moons, terraces, etc. Increases vegetation cover and interception. This influences soil moisture content and grass yields which in turn affect crop and livestock yield.	20 years	Begin October (start rainy season)
Water harvesting	Install a water harvesting structure that captures precipitation (max 50m2) and runoff. Capacity of 5 m^3. Used for irrigation or livestock water in times of dry conditions. Affects crop and livestock yields.	20 years	End May (start dry season)

The behavioral theory Protection Motivation Theory (PMT) (Eq. 1) is applied to simulate whether an agent implements an adaptation measure (m) (Maddux and Rogers, 1983). In this theory, the $\mathrm{IntentionToAdapt}_{t,m}$ is the variable that determines whether an agent will implement a specific measure. Its value is compared with a probabilistic threshold based on the measure's lifespan (See Supplement S1). Crop-related adaptation measures (Table 1) are implemented 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 based on two other components:

$$IntentionToAdapt_{t,m} = \alpha \cdot RiskAppraisal_t + \beta \cdot CopingAppraisal_{t,m}, \tag{1}$$

Risk appraisal includes the perceived probability of the drought risk by the farmers. The perception is high just after a drought event, and then decreases over time. Therefore, risk appraisal increases in relation to drought loss but decreases if no drought loss occurs. Drought loss is computed as the relative loss from decreasing livestock or crop production in a specific year compared to the average production of the previous 10 years (Di Baldassarre et al., 2013).

The perceived ability to adapt (Coping appraisal) is determined by three components: (a) the household's confidence in their ability to implement an adaptation measure (the perceived self-efficacy), which depends on household characteristics such as education level, household size, age, network and gender. (b) the households believe about the relative costs ('perceived adaptation costs') (Van Duinen et al., 2015), and (c) the perceived degree to which the adaptation options are likely to have an effect (perceived adaptation efficacy). The perceived adaptation efficacy, in the model, depends on whether an agent's receive information from extension services or not. 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 the neighboring cells depending on the radius-settings in the model (8-connected if radius = 1).

The adaptation behavioral rules are informed by the survey data from Schrieks et al. (2023). The survey dataset contains information from 502 pastoral and agropastoral households in Isiolo county, Kenya ('Sample area', Fig. 1), and has been collected in May 2022. The dataset contains questions on the intention to adapt for all adaptation measures that are included in the model. The survey also addressed the underlying components of drought risk and coping appraisal of the protection motivation theory. Using survey data and other data sources, we parametrized the model as follows:

- **Household characteristics**: Household characteristics (age, income, etc.) for agents are determined per climate zone (Fig. 1). We initialize agents (crop farmers) located in climate zones I-IV using data of the Tegemeo Institute (2010). Agents in climate zone V (agropastoral communities) are initialized with data by Schrieks et al. (2024). Agents in climate zones VI and VII (pastoral communities) are initialized with data by Schrieks et al. (2023). These initial socio-economic characteristics of agents are based on the best-fitted statistical distribution (e.g. gamma distribution) of the sampled data.
- **Self-efficacy:** We used the household survey data to assess the influence of socio-economic variables (age, gender, etc.) on perceived self-efficacy. For this we estimated Ordinary Least Squares regression (OLS) regressions models (one for each adaptation measure) with as dependent variables the perceived self-efficacy score from the survey and as independent variables the socio-economic variables. We estimate the regression models with multiple different socio-economic variables and included the variables in the model that provided the best the Aike's Information Criteria (AIC) scores (Cavanaugh & Neath, 2019). Supplement S2 gives a description and descriptive statistics of the variables that are used and Supplement S3 provides the regression tables.

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- **PMT weights**: To estimate the weights of the PMT variables in the model, we estimated a logistic regression model with clustered standard errors as in Schrieks et al. (2023). We created composite variables for the coping appraisal variables by taking the average of all adaptation measures in the dataset and we used the binary variable for intention to adapt for all adaptation measures as dependent variables (Schrieks et al., 2023). In Supplement S2 we included a table with an overview of all survey questions that have been used in the regression models.

3.3 Socio-hydrological interactions

Agropastoral households have livestock and cropland. By taking an adaptation measure to fulfil domestic, agricultural or livestock purposes, they change the environment (water availability and land use). Water can be abstracted directly from a river or through groundwater abstraction points for all three purposes.

3.3.1 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). Depending on the season, farmers have to pay for water (Mattijssen, 2022) if there is no water available in their neighbourhood (at walking distance).

3.3.2 Livestock and agriculture

Water demand

Water demand for irrigation is based on the soil moisture deficit (SMD; Equation 4) during the crop growing season, calculated as follows:

$$SMD = D_{root} \cdot (\theta_{fc} - \theta) \quad (2)$$

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. Irrigation water demand is compared to Jeptum et al. (2018) to confirm the correct calibration ranges of the irrigation factor.

Households own livestock, 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 (See Streefkerk et al., 2023).

Crop and grass yield

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Crop and grass yield is calculated based on the ratio between the crop's actual (AET) and potential evapotranspiration (PET) (Ratiocrop_yield; see Supplement S1). This calculation follows Siebert and Döll (2010): if the ratio is 1 (AET = PET), crop yield is at its maximum, while a lower AET reduces crop yield. The crop coefficient kc in the DRYP model, with the reference evapotranspiration, determines a crop's PET. This 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). For determining grass yield, we used crop characteristics of fodder. Actual evapotranspiration indicates how much the crop evaporates based on the current water availability. Crop and grass yield ($Yield_{crop}$) is then calculated by multiplying $Ratio_{crop\_yield}$ with the maximum (irrigated) yield ($Yield_{crop\_max}$) for those two crop types and fodder, following Siebert and Döll (2010):

$$Yield_{crop} = Ratio_{crop\_yield} * Yield_{crop\_max} \quad (3)$$

Income from livestock and crops

We translate crop yield in a year to income by multiplying the yield with market prices of the crops. We address market fluctuations of crops prices by scaling the production of the year to the average production of the last ten years (Wens et al., 2020). We calibrated and verified the simulated maize crop production with data from Kenya's National Information Dashboard on Food Security and Nutrition (KNBS, 2024) of the counties within the model domain, and weighted accordingly. Livestock production (number of animals) is a function of grass yield and calculated on daily basis (Lopez, 2008; Pande and Savenije, 2016). In addition to these rules, we assume a birth rate and that livestock dies if they don't have water for a certain period: for cattle this is four days, while goats can last maximum eight days without water (King, 1983). Income from livestock is generated by selling livestock or milk. Livestock prices are fluctuating by scaling the current livestock production to the average livestock production of the last ten years. Livestock is only sold when a household does not have sufficient income to pay expenses. Milk production is calculated by multiplying the number of animals by the number of litres produced by the type of livestock. For goats this is 1.5 L/day and for cows 3 L/day (Mattijssen, 2022; Otte et al., 2002). Based on Tegemeo Institute (2010) and Mattijssen (2022) region-specific milk and animal prices during different seasons and drought conditions are defined. Simulated milk production of the model is calibrated and verified with milk production data of Laikipia county of the National Drought Management Authority.

3.3.4 Commercial export farms

Commercial export farms are included in the model as water and land users in the upstream areas of the catchment (Fig. 1). Each farm has specific characteristics including: number of grid cells they occupy; a greenhouse roof surface for rainwater harvesting; a reservoir to store water (from roof, river and groundwater); type of farm (flowers or vegetables/other); water abstraction limit (per water source). Commercial farms do not follow the PMT theory for their adaptation decisions, but they try to meet their water demand by using water in the following order: (1) rainwater, (2) open water from rivers, and (3) groundwater. We differentiate between horticulture and crop farm types with the following decision rules:

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- *Commercial horticulture farms*: Commercial farms have a reservoir and a greenhouse. Greenhouses are modelled as 'closed systems' and irrigation water is not added to the model while there is evaporation. Water is used on daily basis from the reservoir to fulfil irrigation requirements, set at 40 m3/hectare/day for flowers (de Hoog, 2001).
    - To fill the reservoir with rainwater, greenhouses catch water on their roofs and store it for later use.
    - If the reservoir is not full and there is water in the river, the reservoir is filled with river water.
    - If there is not enough water in the reservoir and the farm has a permit, then it is filled with groundwater.
- *Commercial crop farms*: Commercial crop farms are modelled similarly to community crop farms in ADOPT-AP (Streefkerk et al., 2023), but it is assumed that these farm types grow wheat. The farms have no rainwater harvesting from greenhouses but can store river and groundwater in a reservoir. They can also directly irrigate from river and groundwater if they have a permit.

Data to characterize the commercial export farms is based on various sources. Dam greenhouse sizes are calculated though Google images. Farm sizes and crop types are obtained from the respective farm websites online. Furthermore, water abstraction limits and permits are specified per commercial farms and are based on abstraction permit data from the Kenya's Water Resources Authority.

3.4 Calibration and validation

Calibration of parameters in all model components is performed using the Distributed Evolutionary Algorithms in Python (DEAP) software (Fortin et al, 2012), which makes use of the Non-Dominated Sorting Genetic Algorithm known as NSGA-II (Deb et al., 2002). Discharge at the outlet of the catchment, milk production, and crop production are the variables used for calibration and validation. The difference between simulated and observed results is evaluated using a modified Kling-Gupta efficiency (KGE) score for discharge (Kling et al., 2012) and the bias ratio (BR; McEvoy et al., 2022) for milk and crop production. The hydrological model has a spin-up period of 11 years (1990-2000). The entire period after the spin-up period is available for calibration (Shen et al., 2022). The calibration algorithm DEAP initiates model runs in the first 'generation', which consists of 60 parameter sets ('individuals'). The values in these sets range as indicated in Table 3. The 10 best performing parameters sets are selected and are either combined ('mated') or altered ('mutated') – with a probability of 0.7 and 0.3 respectively. 12 new 'individuals' are created in the process, and the model is run for these parameter sets. This procedure is repeated 10 times ('generations'). Of all generations, the best performing individual is selected and run to calculate the validation scores (De Bruijn et al., 2023). Table 5 gives an overview of the parameters which are included in the calibration procedure. Note that the hydrology-related parameters are factors that in the model are multiplied by the actual values of the physical parameters. The sensitivity of the hydrological parameters is assessed in Quichimbo et al. (2021), while the other parameters have been assessed by Streefkerk et al., (2023). An exception is the 'intention to behaviour' parameter, which is newly added in this study.

Table 2: Overview of parameters included in calibration procedure.

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Component	Parameters	Values [Unit]
Hydrology	Recession time	0.15 - 0.55 [-]
	Channel saturated hydraulic conductivity	0.2 - 1.0 [-]
	Saturated hydraulic conductivity (unsaturated zone)	0.1 - 0.5 [-]
	Rooting depth	0.6 - 2.0 [-]
	Specific yield	0.01 - 0.2 [-]
	Saturated hydraulic conductivity (saturated zone)	5.0 - 35.0 [-]
Socio-hydrological interactions	Distribution abstraction points	0.1 - 0.9 [-]
	Irrigation factor SMD	0.1 - 2.0 [-]
	Neighborhood radius	1.0-10.0 [km]
Human decision-making	Intention to behavior	0.1-1.0 [-]
	Alpha	0.33-0.66 [-]
	Costs measures	0.5-5 [-]

3.5 Scenario analysis

Three scenarios are run to study the effects of the water and land use of commercial export farms of downstream users:

- *Scenario 1 'Baseline Commercial export farms'*: This scenario is the baseline scenario and includes the current commercial export farms and their operational water management rules (Section 3.1.1).
- *Scenario 2 'Commercial as forest'*: This scenario assumes that the commercial export farms are no longer present, and instead there is a natural forest area. This implies that there is no human water abstraction, and the land use is changed from crop land to forest. To accommodate this in the model, the parameters related to interception (SAVI, fraction vegetation cover and biome specific coefficient), and infiltration capacity (Ksat) are increased in the DRYP model (Ellison et al, 2017; Iacob et al., 2017; Mwangi et al., 2016).
- *Scenario 3 'Commercial as agropastoral communities'*: In this scenario, the commercial export farms are converted into agropastoral communities, similarly to other grid cells, to simulate water and land use during the time before commercial farming was introduced.

We use different drought hazard and impact metrics to assess the effects of the three scenarios. Drought metrics includes soil moisture, discharge and groundwater levels. Drought impact metrics include crop production, milk production, and livestock distance to water of agropastoral communities.

4 Results

4.1 Validation of model

The model is validated by comparing observed and simulated values of three variables (Fig. 4); discharge at the outlet of the catchment, milk production, and crop production (maize). The KGE score of discharge is ~0.54 (composed of a bias ratio of 0.8, variance ratio of 0.74 and Pearson correlation of 0.67), and the BR is ~0.63 for crop production and ~0.62 for milk

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production. The simulated crop production in the best performing parameter set is lower than the observed production, and has a high variability within the ten best performing parameter sets obtained from the genetic calibration method (Section 3.4). The simulated milk production has a higher variability than the observed milk production. However, it follows the timing of the observed peaks very well. During the last period withing the 2020/23 drought the model simulated a lower milk production than was observed.

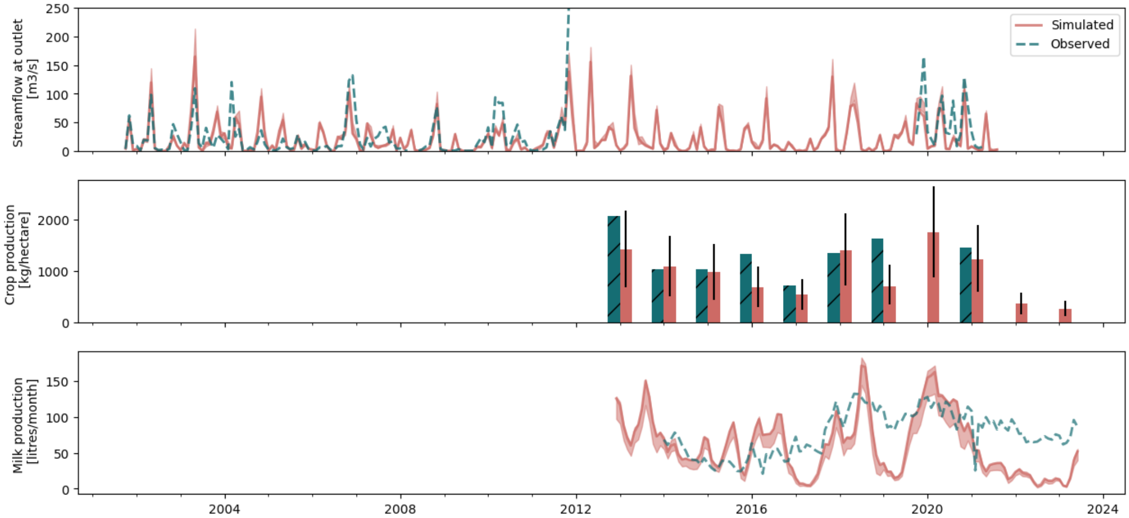

Figure 4: Observed and simulated timeseries of streamflow at the outlet of the catchment (m3/s), crop production (kg/hectare), and milk production (liters/month). The uncertainty ranges indicate the 10th and 90th percentile, resulting from the different parameter sets of the best ten performing runs.

4.2 Scenarios: effect of commercial farming activities on drought risk and impact

Before discussing the effect of different scenarios, we first look at water use by commercial farms in the Baseline scenario. Here, on average, irrigation water use by commercial flower farms is supplied as follows: ~75% of their irrigation is obtained from water that is stored in dams and reservoirs (previously collected via rainwater harvesting on the greenhouse roofs), 7% from river discharge, and 18% from groundwater sources. The irrigation water by commercial crop farms originates for ~35% from river discharge and the remaining ~65% from groundwater sources.

Next, we assess the effects of the three scenarios defined in Section 3.5: (1) Baseline commercial farms (2) Commercial farms converted into forest, and (3) Commercial farms converted in agropastoral communities. To allow for comparison, hazard and impact variables are simulated for two drought periods for each of the three scenarios, but limited to the same months: October 2010 to June 2011 and October 2020 to June 2023. The effects on drought hazard are quantified using the indicators soil moisture, discharge and groundwater elevation. Drought impacts are quantified using distance to water, crop- and milk production.

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4.2.1 Aggregated drought hazard and impact over the drought periods

Figure 5 below shows the average of drought hazard and impact variables for the four sub-catchments where downstream agropastoral households are located, and also excludes the upstream area that was modified in the scenario.

When comparing drought hazard across the two drought periods and scenarios, we mostly see the difference between the two drought periods and less difference across the scenarios. The 2020/23 drought appears to be more severe in terms of soil moisture (0.254, compared to 0.246) and streamflow (2.6 m3/s, compared to 1.3 m3/s) and groundwater depth (110 m, compared to 115 m in the forest scenario. During both drought periods, the groundwater depth is the highest (i.e., lower water table) in commercial farms scenario (112 m in 2010/11 and 119 m in 2020/23). Overall, we can observe that drought hazard is slightly exacerbated in commercial export farms scenario compared to the other scenarios.

In terms of drought impacts, the crop production and milk production is higher in the 2010/11 drought (2010 OND season) compared to the 2020/23 drought (2020, 2021 and 2022 OND season). Crop and milk production during the 2010/11 and 2023/ drought is 609 and 307 kg/hectare for crop production, 24.2 and 26.9 l/month for milk production, respectively. The distance to household water is shorter in the 2010 drought; 120 m for all scenarios. Only in the distance to household water indicator we see notable differences among the scenarios, with the scenario of commercial farms leading to a longer distance to household (266 m) water during the 2020/23 drought indicating that people need to travel further for drinking and sanitation.

While the differences across the scenarios are relatively small, note, however, that we here assess the average effect over a large area, and only look at two time periods. On the other hand, it can be seen that the severity of the drought has a greater impact on households than the difference in scenarios. In the next paragraphs we will have a closer look at the temporal and spatial differences among the scenarios.

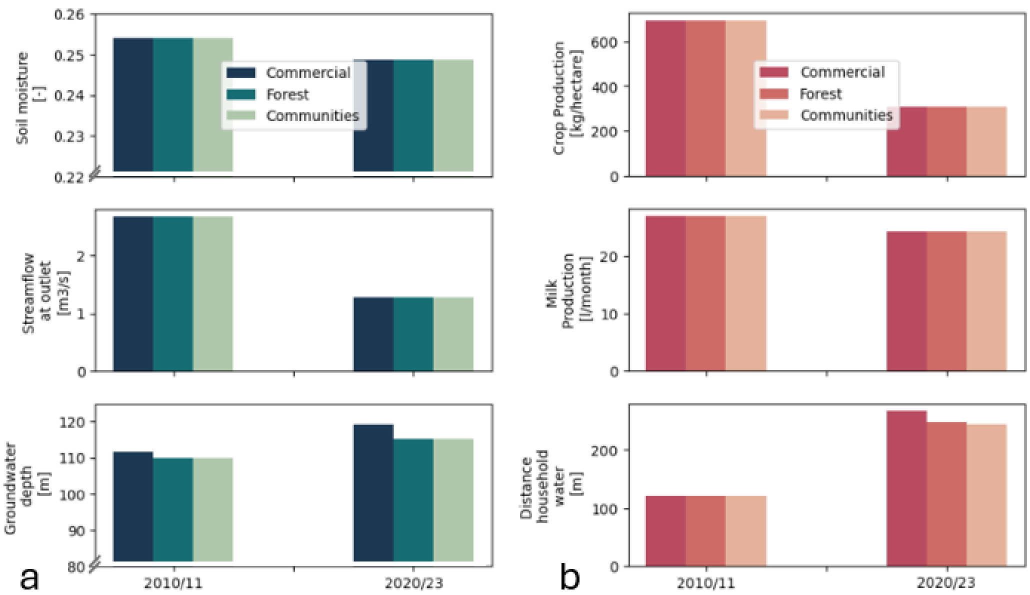

Figure 5: Average of drought hazard (a) and impact (b) over the four sub-catchments for two drought periods in the three scenarios.

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4.2.2 Spatial and temporal drought hazard effects

In this section the three scenarios are assessed in terms of their drought hazard characteristics. Figure 6 shows the effects of the two drought periods by comparing the *forest* (2) and *communities* scenario (3) with the baseline *commercial farms* scenario (1). The figure shows data for the four sub-catchments, excluding the scenario area. Over time the drought hazard variables are positively influenced (i.e. drought hazard reduced) due to the absence of the commercial farms in the *forest* and *communities* scenario. Results show that over time, there is an increase in soil moisture and streamflow. The increase of soil moisture coincided with the timing of the cropping season (OND). Within the scenario area soil moisture is decreased due to less irrigation. During the cropping season less water is abstracted for irrigation in the *forest* and *communities* scenario compared to the *commercial farms* scenario. The higher peaks in soil moisture in the *communities* scenario compared to the *forest* scenario can be explained by the higher adoption of irrigation or agroforestry by households, which is lower in the *forest* scenario (see Supplement S4). Groundwater tables are up to 1,5m higher in both the *forest* and *communities* scenarios. This effect is caused by the absence of abstraction of groundwater by the farms, and more infiltration because of the absence of greenhouses covering the land surface, causing less water taken out of the groundwater and an increase in groundwater recharge. In the *forest* scenario the infiltration capacity is higher, leading to higher groundwater tables. In the *communities* scenario, wheat is grown at the open farms instead of maize or casava, which results in different water demands. Streamflow and soil moisture are hydrologically connected to the groundwater table, which can explain the same upward trend in all the three variables. Note that there is no increase in groundwater level in absolute terms, but the increase is relative to the commercial farms scenario, which has a decreasing trend due to abstraction. Absolute values of the hydrological variables can be found in Supplement S5.

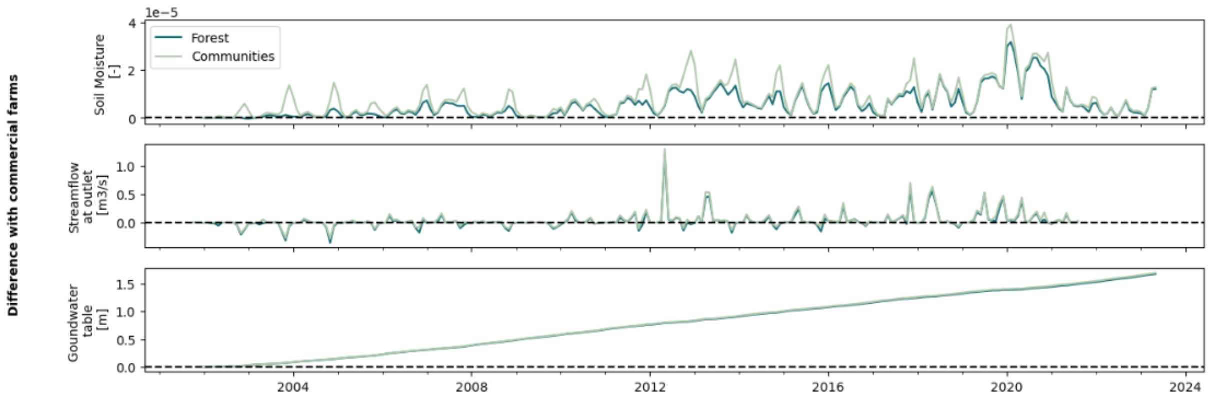

Figure 6: Differences between baseline commercial farms (scenario 1), and forest (scenario 2) and communities scenario (scenario 3) in soil moisture (-), discharge (m^3/d) and groundwater level (m) aggregated over the four sub-catchments, excluding the scenario area.

Figure 7 also shows these effects spatially over the whole drought period of 2020-2023. The left panels shows that the decrease in soil moisture is largely at the location of the commercial farms in the *forest (2)*- and *communities (3)* scenarios during the whole drought. However, interestingly, there is an increase of soil moisture at some riparian zones downstream within the

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same sub-catchments, which is linked to the increase in streamflow (**Error! Reference source not found.**, middle) d ownstream of the commercial farms. Some areas in the most Eastern sub-catchment have a reduction of streamflow. Furthermore, the figure shows that the increase of the groundwater table is mostly observed around commercial farms in both *forest* and *communities* scenario (around 5 meter over the 2020/23 period), as explained in previous paragraph. The increase of the groundwater has an effect downstream: a rise of the groundwater table downstream of the scenario area (around 1 meter over the 2020/23 period). There is no significant difference between the *forest* and *communities* scenarios, indicating that the commercial farms are most influential in modifying drought hazard characteristics.

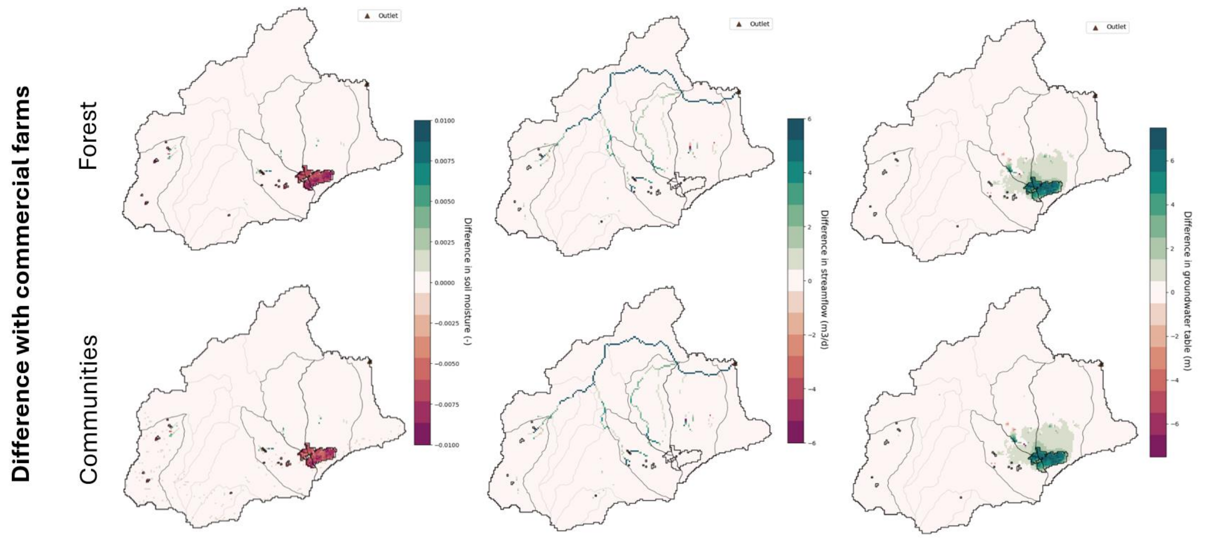

Figure 7: Differences between commercial farms and forest scenario (2) and communities scenario (3) over the 2020-23 drought period using hazard indicators: soil moisture (-), discharge (m^3/d), and groundwater table (m).

4.2.2 Spatial temporal drought impacts

The spatial and temporal effects of the three scenarios are assessed in terms of their drought impact characteristics. We zoom in to role of different agents types: effects on crop production are assessed separately for agents close to the river and those located further away. Milk production differences are assessed separately for agents that migrate with their livestock (to seek for better pastures) and those who do not.

Error! Reference source not found. shows the differences in crop production for *forest* scenario and *communities* scenario a s compared to the baseline *commercial farms* scenario. Average crop production is higher for agents located nearby a river stream, which enhances water access, especially in the drought periods at the end of the years 2010, 2015, and 2021. Crop production shows less difference with the baseline in forest scenario than in the *communities* scenario. Note that the percentage change is relatively low (maximum of 0.4%).

The *forest* and *communities* scenarios increase milk producton in the period between 2017 and 2023 for agents who migrated with livestock; up to 20 l/month. The peak in milk production matches the peak in soil moisture (**Error! Reference source n**

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ot found.). Higher soil moisture results in higher grass produciton, leading to higher milk production. On the other hand, agents who did not migrate are (slightly) negatively influenced in that period in the *forest* and *communities* scenario. The reason could be that other agents who migrated, accessed the area of agents who stayed and therefore grass yields are shared among more livestock numbers, resulting in lower milk production. The phenomana can also explain the 'mirroring' of the results; if people who migrated have a higher milk production the people who did not migrate have a lower milk production (for example in the period before 2004). However, in the period before 2016 and after May 2013 a decrease in milk production can be observed for the agents who migrated (up to 10 l/month). In both the *forest* and *community* scenario around 5% more people migrated that season, compared to the *commercial farms* scenario (see Fig. S4 in the Supplement). Decisions whether to migrate or not are made beginning of May. It could be that less grass and water was available that upcoming dry season (end May to end September 2013), than was expected based on the conditions beginning of May (FEWSNET, 2013) resuling in lower milk production. This situation could have been different in the commercial farms scenario, as in general less water and grass was available.

The distance to household water is decreased in *forest* and *communities* scenarios during the dry season, but this distance increases in the rainy season. The distance to household water is influenced by both the streamflow and groundwater level. An higher variability of distance to household water can be observed with the agents located near a river. The distance to household water follows a similar pattern as the streamflow (Fig. 6); an increase in streamflow results in a decrease in distan ce to household water and vice versa.

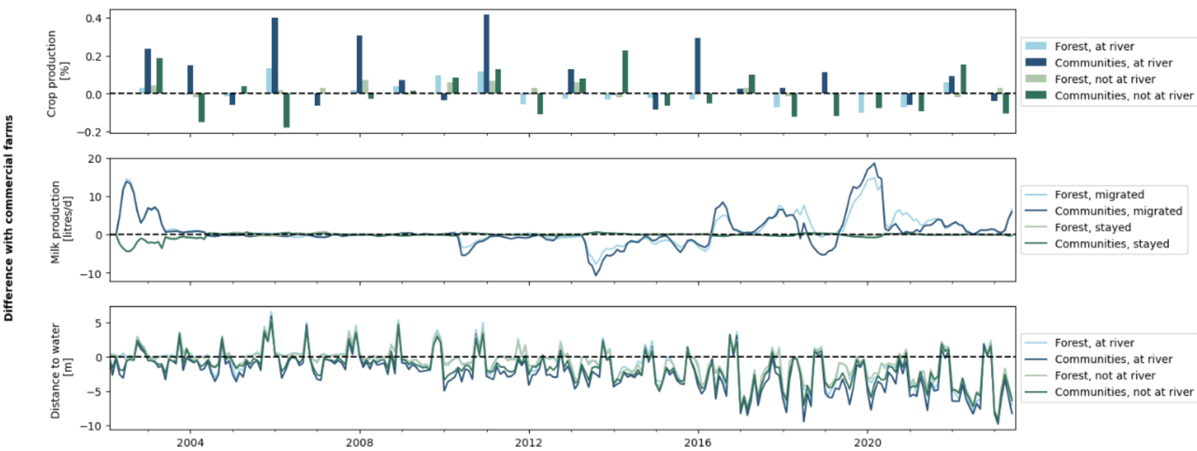

Figure 8: Difference in forest and communities scenario compared to commercial farms scenario, expressed in crop production (kg/hectare), milk production (liters/d), and distance to household water (m). The figure also shows the impacts differentiated between agents located at the river (for crop production and distance to household water) and whether they migrated or not (for milk production).

5 Discussion

5.1 Influence of commercial export farms on drought hazard and impact

Previous research has already shown that water abstraction by commercial export farms reduces streamflow during the dry season. For example, Lanari et al. (2018) found that streamflow in Naru Moru River (tributary within the Ewaso Ng'iro catchment) are influenced by commercial export farms in the catchment, resulting in to up to 32% of streamflow reduction in the month of February (dry season). This study has comparable results for the Naru Moru with an average reduction of 22% in February in the period of 2002 to 2012. In the period of 2013 to 2023 in February we see a decrease in streamflow of 36% in the Naru Moru River. It is, therefore , expected that the ongoing expansion of commercial export farms will result in a further reduction of streamflow if no further water saving measure will be taken (Lanari et al., 2018).

On top of these common findings for streamflow effects, our results show a large effect of commercial farms lead to lower groundwater tables. Initially, groundwater levels may appear sufficient to support both commercial farming activities and local community needs. As groundwater is a hidden water source and there is a lack of groundwater monitoring, it may be difficult for communities and practitioners to perceive the extent of the problem. Additionally, the immediate economic benefits from export farming, such as employment opportunities and increased local revenue, may overshadow concerns about water consumption. Over time, the excessive withdrawal of groundwater may lead to unsustainable water management (Gaye & Tindimugaya, 2019) and thus high impacts in the long term (Hogeboom et al., 2015). Impacts may include wells running dry for domestic use, inequity in access to water, land subsidence, conflict, and ecosystem and biodiversity degradation (Perrone & Jasechko, 2017; Rafiei Emam et al., 2015; Sarkar, 2012).

To mitigate these long-term impacts, it is essential to implement sustainable water management practices that balance the needs of commercial and local water users, including; i) Regulating (indirect) water use by enforcing existing regulations and/or establishing robust groundwater monitoring systems and regulations to ensure that extraction rates do not exceed recharge rates and abstraction permit limits. Not only for commercial export farms, but (illegal) water abstraction in general (Mwaura et al., 2021); ii) Supporting the implementation of sustainable agricultural practices. The adoption of water-efficient irrigation methods can be encouraged to reduce water consumption (Mulwa et al., 2021). Alternatively, water consumption can be decreased by decreasing bare soil evaporation through promoting soil moisture conservation techniques such as agroforestry (Mwangi et al., 2016) and mulching (Kader et al., 2019); iii) Promoting equitable water distribution (especially in dry periods) by involving local communities in water management decisions and raising awareness about the importance of sustainable water use. The governance structure of the WRUA's is already a step forward in equitable water distribution (Dell Angelo et al., 2016; Mwaura et al., 2021).

When reviewing experiences from drylands in other global regions, the question is whether producing water intensive commodities can be a sustainable water management practice in water-scarce dryland areas (Martinez-Valderrama et al., 2024). Especially when the commodity is exported and not contributing to the food security of the country itself. However, this is a political discussion, as there are also employment and economic benefits to this industry (Peter et al., 2018; Mekonnen et al, 2012). In addition, the importing countries can take virtual water (or energy) footprints into account in their supply chain (Mekonnen et al, 2012).

5.2 Drought impacts and human-water feedbacks

Drought impacts are a manifestation of complex system in which interaction between water and people exist and emerge (Van Loon et al., 2016). Drought impacts may be different for different people, as people have different capacities or respond differently. In turn, the drought responses of people (and other actors) may influence the propagation of drought. For example, irrigation may delay the drought impact of soil moisture drought, but may worsen the drought at a later stage during hydrological drought (Piemontese et al., 2024). Other feedbacks relate to behavioural factors. For example, results show seasonal migration dynamics, and how people influence each other's pasture availability and milk production. Lower milk production in one year, may increase risk perception for the next year and thus the chance of migrating. The scenario analysis shows that the uptake of irrigation and agroforestry is lower in the forest scenario as compared to the scenario with commercial farms. This is probably due to the higher water availability in the scenario without commercial farms leading to a lower risk perception, resulting in a lower uptake of irrigation. Understanding these interactions is crucial for developing effective drought adaptation strategies for agropastoral communities, and sustainable water management practices and governance (Wens et al., 2021).

There is a broader scientific discussion on the (human-induced) conversion of agricultural land into forest, and what the effect is on (downstream) hydrology (Ellison et al., 2012). Some studies see forests as 'demanders' of water (through higher evapotranspiration rates) (Greeff, 2010; Malmer et al., 2010; Trabucco et al., 2008), while other see them as 'providers' (through moisture transport, higher infiltration and lower soil evaporation) (Ellison et al., 2017; Sheil & Murdiyarso, 2009). In this study, the scenario analysis excludes the scenario area itself from the analysis and focusses on downstream effects, where we do see small differences. As mentioned in the results, soil moisture is higher in the *communities* scenario during the cropping season. It can be due to a higher uptake of irrigation and agroforestry, but it can also be because of different hydrological fluxes. When looking into the hydrological fluxes over the entire catchment, higher canopy evaporation can be observed in the *forest* scenario, resulting in lower potential evaporation and precipitation reaching the soil. Insignificant changes are observed in groundwater storage and recharge. The model does not take any potential benefits of moisture recycling of forest into account. Keeping the human-drought feedbacks of adoption behaviour in mind, it is difficult to point out what causes the higher soil moisture; the higher uptake of adaptation measures or changes in hydrological fluxes. Future research would be needed for that.

The development of models like ADOPT-AP provides a valuable tool for capturing and understanding the interactions between human activities and drought impacts. However, lack of data on adaptation measures over time hinders the validity of modelling the effects of adaptation measures as human-water feedbacks (Aerts, 2020). Although alternative calibration parameters can be used to calibrate and validate the model, empirical longitudinal data from consecutive surveys on the uptake of adaptation measures would be valuable (Kalthof et al., 2024). Such panel data would give more certainty around calibrating the weighting of relative importance of the risk and coping appraisal parameters in our decision model and the threshold that drives the intention to adapt to measures actually implemented (Bubeck et al., 2020).

In this study households and commercial farms are incorporated as actors that influence the water balance. However, other water users may be important as well, especially considering population growth in urban areas (Wamucii et al, 2023) and the expansion of the tourism industry (Mutiga et al., 2010). Furthermore, this study represents the adaptive behaviour of households through the protection motivation theory (PMT). Although research shows that PMT factors best explain the adaptive behaviour of farmers in Kenya (Wens et al., 2021), it should be noted that not all factors are included in this study and more factors may influence the adoption of drought measures (Schrieks et al., 2023).

Conclusion

This study presents an evaluation of the effects of commercial export farms in terms of drought hazard and impacts within the Upper Ewaso Ng'iro catchment. After validation of the model, we compared the base scenario in which commercial farms are present in part of the catchment to two scenarios where there are agropastoral communities or forests instead of the commercial farms.

The analysis shows that in the scenarios where these farms are replaced by forests or communities, drought conditions are alleviated by increased soil moisture, streamflow, and groundwater tables during dry periods. These improvements of drought conditions are related to reduced water abstraction and increased infiltration of communities and forests compared to commercial farms. This benefits downstream communities by decreasing the distance to household water (average up to 10 m) and increasing crop production (average up to 0.4 %) and milk production (average up to 10 l/ month) in times of drought. Changes are, however, low in comparison to the effect of drought itself.

The reduction of streamflow due the commercial farms aligns with previous research, highlighting the need for equitable water management practices. Policy interventions should prioritize equitable water distribution, regulation of water use, and promotion of sustainable agricultural practices to mitigate long-term impacts on water resources and community resilience.

Code and data availability

The ADOPT-AP model code is publicly available in GitHub via https://github.com/istreefkerk/ADOPT-AP and http://doi.org/10.5281/zenodo.7447665.

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Author contribution

IS, JB, AL, JA; conceptualization. IS, JB, AL, JA, TS; writing – original draft. IS; methodology and visualization. JB IS: software. TS: formal analysis. JB, AL, JA supervision. RO, KH, OW, investigation. KH, RO, OW: writing – reviewing & editing.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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