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Education, financial aid and awareness can reduce smallholder farmers' vulnerability to drought under climate change

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Abstract. Analyses of future agricultural drought impacts require a multidisciplinary approach in which both human and environmental dynamics are studied. In this study, we applied the agent-based drought risk model ADOPT to assess the effect of various drought risk reduction interventions on smallholder farmers in the Kenyan drylands. Moreover, the robustness of these (non-)governmental interventions under different climate change scenarios was evaluated. ADOPT simulates water management decisions of smallholder farmers, and evaluates household food insecurity, poverty and emergency aid needs due to drought disasters. Model dynamics were informed by extensive field surveys and interviews from which decision rules were distilled based on bounded rational behaviour theories.

Model results suggest that extension services increase the adoption of low-cost, newer drought adaptation measures while credit schemes are useful for cost-effective but expensive measures, and ex-ante cash transfers allow the least wealthy households to adopt low-cost well-known measures. Early warning systems show more effective in climate scenarios with less frequent droughts. Combining all four interventions displays a mutually-reinforcing effect with a sharp increase in the adoption of measures resulting in reduced food insecurity, decreased poverty levels and drastically lower need for emergency aid, even under hotter and drier climate conditions. These nonlinear synergies indicate that a holistic perspective is needed to support smallholder resilience in the Kenyan drylands.

Key words: Agent-based modelling, drought disasters, risk reduction, adaptation measures, adaptive behaviour, smallholder farmers, AquacropOS, ADOPT, drought risk reduction; Kenya, dryland agriculture

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1 Introduction

Droughts, defined as below-normal meteorological or hydrological conditions, are a pressing threat to the food production in the drylands of Sub-Saharan Africa (Brown et al., 2011; Cervigni & Morris, 2016; UNDP et al., 2009). Over the last decades, increasing temperatures and erratic or inadequate rainfall have already intensified drought disasters (Khisa, 2017)limate change, population growth and socio-economic development will lead to additional pressures on water availability (Erenstein, Kassie, & Mwangi, 2011; Kitonyo et al., 2013). In Kenya, three quarters of the population depends on smallholder rain-fed agricultural production and nearly half of the population is annually exposed to re-occurring drought disasters causing income insecurity, malnutrition and health issues (Alessandro et al., 2015; Khisa, 2018; Mutunga et al., 2017; Rudari et al., 2019; UNDP, 2012). Reducing drought risk is imperative to enhance the resilience of the agriculture sector, to protect the livelihoods of the rural population, and to avoid food insecurity and famine in Kenya's drylands (Khisa, 2017; Shikuku et al., 2017).

Drought risk models are important tools to inform policy makers about the effectiveness of adaptation policies and enable the design of customized drought adaptation strategies under different future climate scenarios (Carrao et al., 2016; Stefano et al., 2015). Traditionally, such models express disaster risk as the product of hazard, exposure and vulnerability, and are based on historic risk data. Recent disaster risk models have dealt with climate change adaptation in a two-stage framework; first describing the adaptation choices of representative households, then estimating the impacts of adaptation on (future-) welfare while assuming climate change scenarios (di Falco, 2014). However, most existing research does not account for vulnerability dynamics, the heterogeneity in human adaptive behaviour, and its feedbacks on drought risk while it are these aspects that determine, for a large part, the actual risk (Eiser et al., 2012).

Uncertainties in adaptive behaviour are often addressed by using different adaptation scenarios, but this approach fails to capture the two-way interaction between risk dynamics and adaptive behaviour dynamics (Elshafei, 2016). It appears that farmers often act bounded rational towards drought adaptation rather than economically rational: their rationality in limited in terms of cognitive capability, information available, perceptions, heuristics and biases (Schrieks et al., 2021; Wens et al., 2021). To account for such individual adaptive behaviour, an agent-based modelling technique can be applied (Berger & Troost, 2014; Blair & Buytaert, 2016; Filatova et al., 2013; Kelly et al., 2013; Matthews et al., 2007; Smajgl et al., 2011; Smajgl & Barreteau, 2017). Agent-based models allow explicitly simulation of the bottom-up individual human adaptation decisions, and capture the macro-scale consequences that emerge from the interventions between individual agents and their environments. Combining risk models with an agent based approach is thus a promising way to analyse drought risk, and the evolution of it through time, in a more realistic way (Wens et al., 2019).

Here we present how an innovative dynamic drought risk adaptation model, ADOPT, can increase our understanding of the effect of drought policies on community-scale drought risk for smallholder farmers in Kenya's drylands. ADOPT combines drought risk and agent-based modelling approaches by coupling the FAO crop model AquacropOS with a decision making model, which is parameterized following the Protection Motivation theory (PMT) – a psychological theory often used to model farmer's bounded rational adaptation behaviour (Schrieks et al 2021). This theory describes how individuals adapt to shocks

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such as droughts, and are motivated to react in a self-protective way towards a perceived threat (Grothmann & Patt, 2005; Maddux & Rogers, 1983). The PMT suggests that the motivation to protect (in this study farmers' intention to adopt a new adaptation measures), is defined by a persons' risk appraisal (their risk perception, experiences of risk events in their social networks…) and the perceived options to cope with risks. The latter is related to different factors such as: perceived self-efficacy (assets and sources of income, education level, family size…), adaptation efficacy (land size, adaptation measure characteristics) and adaptation costs (expenses in relation to their income) (Gebrehiwot & van der Veen, 2015; Keshavarz & Karami, 2016; van Duinen et al., 2015, 2016a).

In this study, we test the variation in household drought risk under different drought management policies: (i) a reactive government only providing emergency aid, (ii) a pro-active government, which supports ex-ante cash transfer in the face of droughts and sufficient drought early warnings, and (ii) a strategic government that supports adaptation credit schemes and provides regular drought adaptation extension services to farmers. In addition, future drought risk and the robustness of the policies are evaluated under different climate change scenarios.

2 Case study description

The ADOPT model has been applied to the context of dryland communities such as Kitui, Makueni or Machakos in south-eastern Kenya (fig. 1). This semi-arid to sub-humid region is drought-prone, being hit by drought disasters in 1983/84, 1991/92, 1995/96, 1998/2000, 2004/2005, and 2008-11, 2014-2018 (data from Em-DAT and DesInventar). While the majority of the population in this dry transitional and dry mid-altitude maize farming zone is directly or indirectly employed through agriculture, technology adoption and production level remain rather low, making the region very vulnerable to droughts and climate change (Khisa & Oteng, 2014; Mutunga et al., 2017).

In Kenya, 75% of the countries' maize is produced by smallholder farms, maize production employs 25% of the agricultural labourers, and over 97% of the farmers grow it, mainly for own consumption or local markets (Brooks et al., 2009; Kariuki, 2016; Nyariki & Wiggins, 1997). It is the main staple food for the people, providing more than a third of the caloric intake, and is also the primary ingredient used in animal feeds in Kenya (Adamtey et al., 2016; FAO, 2008). While reported smallholder farm maize crop yields often do not exceed 0.7 ton/ha, with optimal soil water management maize yield can easily be around 1.3 ton/ha in the semi-arid medium potential maize growing zone in south-eastern Kenya (Omoyo et al., 2015).

In the south-eastern Kenyan dry mid-altitude farming zone, smallholder farmers produce ten to twenty 90kg bags of maize per year grown in the two rainy seasons to ensure adequate supplies to meet household food needs (Erenstein, Kassie, & Mwangi, 2011; Erenstein, Kassie, Langyintuo, et al., 2011; Speranza et al., 2008). While during the long rainy season (March-April-May) multiple crops are planted, the short rainy season (October-November-December) is considered the main growing season for maize in the region (Rao et al., 2011). Only about 20% of the farmers is able to sell their excess crops, while 66% has to buy maize to complement their own production (Muyanga, 2004). Few farmers use pesticides or improved seeds or other adaptation stragegies (Tongruksawattana & Wainaina, 2019). In Kitui, Makueni and Machakos, the most preferred seed-variety

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is the high yielding but less drought resistant Kikamba/Kinyaya variety (120 growing days) with a potential yield of only 1.1 tons per hectare (Speranza, 2010; Recha et al., 2012). Trend analysis (1994-2008) shows that yields are declining due to the increasing pace of recurring droughts (Nyandiko, 2014).

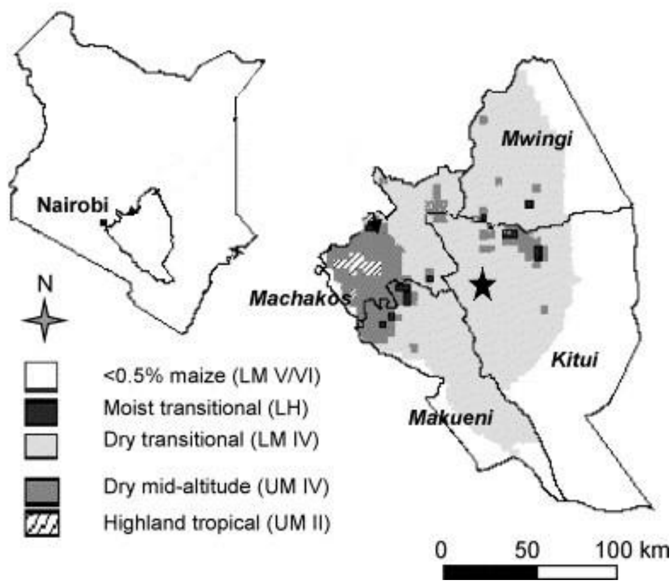

Figure 1: South Eastern Kenya maize agro-ecological zones. Area of survey data (Wens 2021) indicated with a star. Map adjusted from Barron and Okwach (Barron & Okwach, 2005)

3 Model and scenario description

ADOPT (fig. 2, Wens et al 2020, adjusted ODD+D protocol in Appendix A) is an agent-based model that links a crop production module to a behavioural module evaluating the two-way feedback between drought impacts and drought adaptation decisions. For this study, ADOPT was parameterized with information from expert interviews, a farm household survey with 250 households and a discrete choice experiment executed in the Kitui Region, Kenya (Wens et al. 2021). This empirical data-set feeds the decision rules in ADOPT, which enables describing farm households' adaptive behaviour in the face of changing environmental conditions (drought events), social circumstances (farmer networks), and (non-)governmental interventions (drought management policies) conditions. In ADOPT, crop production is modelled using AquacropOS (Foster & Brozović, 2018), simulating crop growth on a daily basis and producing crop yield values at harvest time twice per year. Calibrated for the Kenyan dryland conditions (Ngetich et al., 2012; Wamari et al., 2007), ADOPT takes into account the current water management of the farm and yields vary with weather conditions. The adaptive behaviour of the farm households (agents) is modelled based on the Protection Motivation theory (PMT, Rogers 1975), which was derived as most suitable in an earlier study (Wens et al, 2020) and has proved to best describe the observed behaviour of farm households (Wens et al 2021). In this application of ADOPT, the model was run over 30 historic years as baseline then 30 years of scenario, using 12 different initialisations to allow for uncertainty in the relative importance of the behavioural factors.

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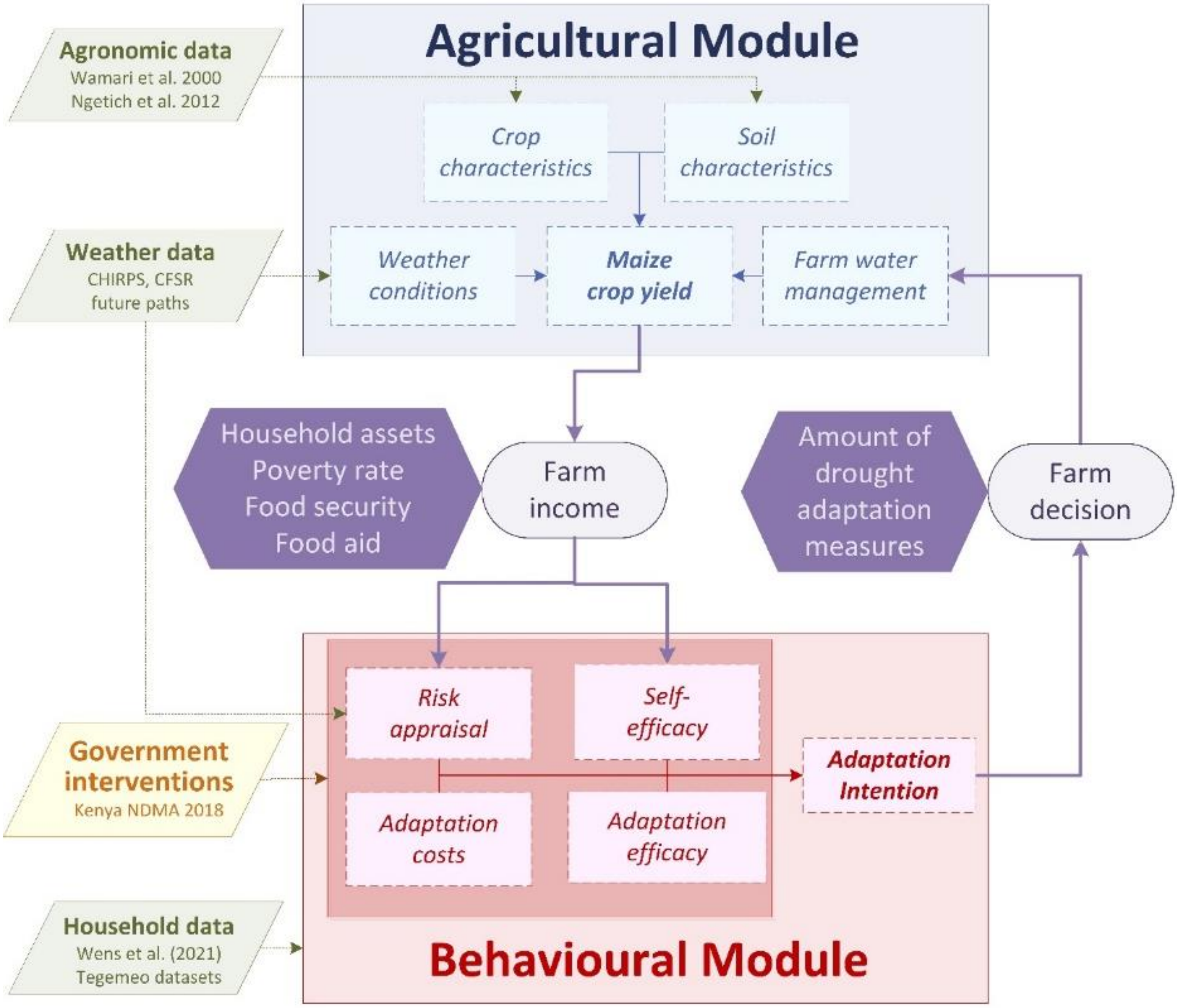

Fig. 2: ADOPT model overview, adjusted from Wens et al., 2020**. Description of the model in Appendix A.**

3.1 Individual adaptive behaviour in ADOPT

Various soil water management practices can be adopted by smallholder farmers in ADOPT: drip irrigation infrastructure, or shallow wells to provide irrigation water, and Fanja Juu terraces as on-farm water harvesting techniques. Moreover, soil protection such as mulching is included. These measures are beneficial in most – if not all – of the years, and have a particularly good effect on maize yields in drought years, but current adoption rates of these measures are quite varied and often remain rather low (Gicheru, 1990; Kiboi et al., 2017; Kulecho & Weatherhead, 2006; Mo et al., 2016; S. Ngigi, 2019; S. N. Ngigi et al., 2000; Rutten, 2004; Zone, 2016).

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Applying the PMT and using the empirical regression and correlation results of the households dataset, ADOPT models four main factors determining farmers' adaptation intention under risk: (1) risk perception is modelled through the number of experienced droughts and number of adopted measures, household vulnerability, and experienced impact severity. Moreover, thrust in early warnings is added, which can influence the risk appraisal if a warning is send out. Coping appraisal is modelled through a (2) farmers' self-efficacy (household size / labour power, belief in god, vulnerability), (3) adaptation efficacy (perceived efficiency, cost and benefits, seasons in water scarcity, choices of neighbours, number of measures), and (4) adaptation costs (farm income, off-farm income, adaptation spending, access to credit). These four PMT factors receive a value between 0 and 1 and define a farmer's intention to adopt. Which smallholder farmers adopt which measures in which years is then stochastically determined based on this adaptation intention. Through a sensitivity analysis on the relative weights of the factors, both the average effect of individual adaptation decisions and its standard deviation are analysed (Wens et al 2020).

3.2 Drought risk indicators in ADOPT

In ADOPT, Annual maize yield influences the income and thus assets of the self-sufficient farm households. This influence is indirect, because the farm households are assumed to be both producer and consumer, securing their own food needs. And it is direct, because they sell their excess maize on the market at a price sensitive to demand and availability. Farm households who cannot satisfy their food needs by their own production, go to this same market and buy the needed maize – if they can afford it and if there is still available. If they cannot or if there is a market shortage, they are deemed to be food insecure, and their food shortage is multiplied by the market price to estimate their food aid needs. Adding the farm income of the household with their income from potential other sources of income, it is estimated whether they fall below the poverty line. As climate and weather variability let maize yields fluctuate over time, so do the prevalence of poverty, the share of households in food insecurity and the total food aid needs. These factors can be seen as proxies for drought risk and were evaluated over time.

3.3 Climate change scenarios

Multiple climate change scenarios – all accounting for increased atmospheric carbon dioxide levels - were tested: a rising temperature of 10%, a drying trend of 15%, and a wetting trend of 15%, and various combinations of these. The warming and drying trends were based on a continuation of the trends existing in the last 30 years of daily NCEP temperature (Kalnay et al., 1996) and CHIRPS precipitation (Funk et al., 2015) data (authors' calculations). The wetting trend was based on the projections from most climate change models which predict an increase of precipitation in the long rain season – a phenomenon known as the 'East African Climate Paradox'(Gebrechorkos et al., 2019; Lyon & Vigaud, 2017; Niang et al., 2015). The no change scenario was a repetition of the baseline period, without changing precipitation or temperature hence only elevated carbon dioxide levels. Reference evaporation was calculated for each scenario using the Penman-Monteith model and thus influenced by temperature changes (Allen, 2005; Droogers & Allen, 2002).

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Table 1: Average (daily temperature, annual precipitation) weather conditions (1980-2010) in ADOPT

	min temperature	max temperature	precipitation	reference evaporation
No change	16.3 (+- 0.8) *C	26.9 (+- 0.9) *C	888 (+-319) mm	1547 (+-298) mm
Wet	16.3 (+- 0.8) *C	26.9 (+- 0.9) *C	1021 (+-367) mm	1547 (+-298) mm
Hot	17.9 (+- 0.9) *C	29.6 (+- 0.9) *C	888 (+-319) mm	1659 (+-320) mm
Dry	16.3 (+- 0.8) *C	26.9 (+- 0.9) *C	755 (+-271) mm	1547 (+-298) mm

These trends were added to time series of 30 years of observed data, so as to simulate credible events and have a realistic day-to-day, month-to-month and even decadal variability. This resulted of 30 years of 'future' data, for each of the six - wet, hot-wet, hot, dry, hot-dry and no change - scenarios . While such scenarios might not have a probability of occurring , as a possible change in frequency and extremeness of events is ignored, they allowed testing the robustness of the farmer and government drought adaptation strategies under changing hydro-meteorological conditions. This application of ADOPT ran over thirty years of baseline and then thirty years of climate change scenarios; its change indicated as "Year 0".

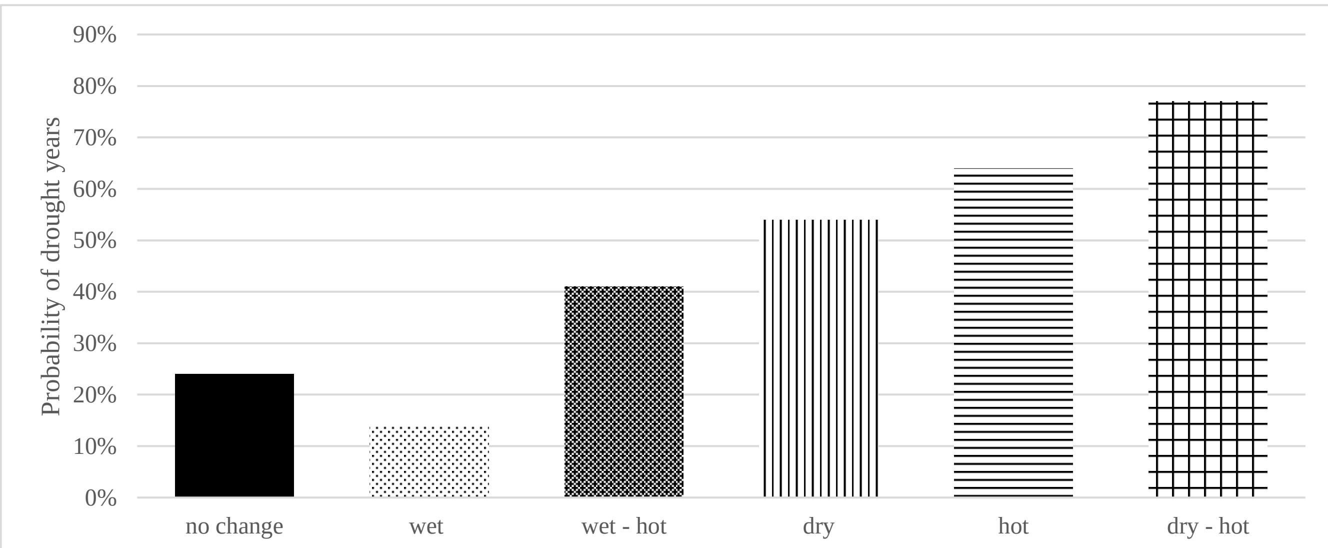

Fig. 3: Probability of having a year with three or more consecutive months under a SPEI < -1, for the climate change scenarios.

Droughts, here defined as at least three months with standardized precipitation index (SPEI) values below – 1 , have a different rate of occurrence under these different future climate scenarios (Fig. 3). SPEI is calculated through standardizing a fitted GEV distribution over the historic monthly time series, and superimposing this onto the climate scenario time series. Under the no change scenario, 59 months between 2015-2045 fall below this threshold, this is lowered to 34 months under the wet scenario. Under hot conditions, the number of drought months more than doubles to 123 months. Temperature is dominant over precipitation is determining drought conditions, as under the hot-wet scenario, 97 drought months are recorded, and even 157 under hot-dry conditions.

3.4 Drought risk reduction intervention scenarios

Farmers' adaptive behaviour can be influenced by external policies and (non-)governmental drought risk reduction interventions. Kenya Vision 2030 for the ASAL promotes drought management through extension services, and aims to increase access to financial services such as affordable credit schemes (Government of Kenya, 2012; Kenya, 2016). Furthermore, building on the Ending Drought Emergencies plan, the National Drought Management Authority prioritizes the customization, improvement and dissemination of drought early warning systems, and aims to establish trigger levels for ex-ante cash transfer so as to upscale drought risk financing (Government of the Republic of Kenya, 2013; National Drought Management Authority, 2015; Republic of Kenya, 2017). Improved extension services tailored to the changing needs of farm households (Muyanga & Jayne, 2006). a better early warning system with longer lead times (Deltares, 2012; van Eeuwijk, n.d.), ex-ante cash transfers to the most vulnerable when a drought is expected (Guimarães Nobre et al., 2019) and access to credit-markets (Berger et al., 2015; Fan et al., 2013), are all assumed to increase intention to adopt new measures.

As shown in Wens et al (2021), extension services are best offered to younger, less rich and less educated people, or to who already adopted the most common measures, to have a big influence on the adoption intentions. Similarly, early warning systems are appreciated more by less educated, less rich farmers, or those not part of farmer knowledge exchange groups. The ex-ante cash transfer instigates those who spend already a lot of money on adaptation, to adopt more expensive measures the most. Access to credit is preferred by less rich farmers, how have a larger land size, are member of a farm group, went to extension trainings, have easy access to information and/or are highly educated (Wens et al. 2021).

In this application of ADOPT, the effect of these four interventions - extension services, early warning systems, ex-ante cash transfer and credit schemes - were tested individually. Additionally, three scenarios, combining different types of interventions, were evaluated, all initiated in year "0" in the model run:

1. Reactive (non-)governmental intervention "supporting drought recovery": Emergency aid is given to farmers who lost their livelihoods after drought disasters; this food aid is distributed to farmers who are on the verge of poverty to avoid famine.
2. Pro-active (non-)governmental intervention plan "preparing for drought disasters": Early warnings are sent out each season if a drought is expected. This is assumed to raise all farmers' risk appraisal with 20%. Ex-ante cash transfers are given to all smallholder farmers (those without income off-farm and without commercialisation) to strengthen resilience in the face of a drought. This is done when severe and extreme droughts (SPEI <-1, and <-1.5) are expected that could lead to crop yield lower than respectively 500kg/ha and 300kg/ha. Money equivalent to the food insecurity following these yields is paid out to farmers with low external income sources. Lastly, emergency aid is given to farmers who need it.
3. Strategic (non-)governmental intervention plan "mitigating drought disasters": Credit rates are lowered so that it is affordable to people to take a loan for adaptation measures, at an interest rate of 2% and a pay-back period of five year. Besides, frequent trainings are given in communities with poor practices to improve their human capacity related to drought adaptation practices for agriculture. Moreover, like in the pro-active government scenario, an improved early warnings system is set up and ex-ante cash transfer is given. Lastly, emergency aid is given to farmers who need it.

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4. Results

The annual average maize yields under the different climate scenarios, for all of the water management measures that can be adopted by the smallholder farmers - mulch, fanya juu bunds, shallow wells and drip irrigation -, were calculated using AquacropOS (Fig. 4). Under wetter future climate conditions, maize yields are expected to increase under all management scenarios, with mulch having a particular positive effect on the soil moisture conditions throughout the full growing season. Hotter climate conditions reduce yields slightly, and the assumptions in this model on the frequency and amount of manual irrigation or drip irrigation water are not sufficient to diminish this effect, even under wetter conditions. Paired with drier conditions, this hotter future has dramatically negative effects on yields, showing on average 28% lower yields compared to the no climate change scenario over all management scenarios.

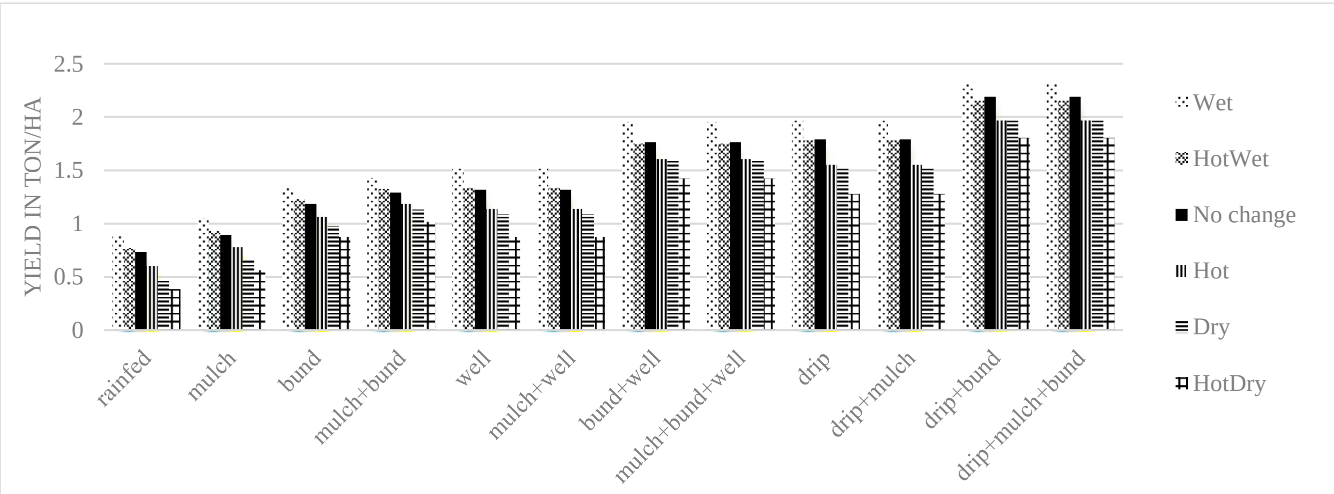

Fig. 4: Average maize yield under different agricultural water management conditions and different future climate scenarios.

In ADOPT, all evaluated (non-)governmental interventions increased the adoption rate of the evaluated adaptation measures compared to the reactive "no intervention" scenario. This means that adaptation intention is indeed limited by a low risk perception, high (initial) adaptation costs, a limited knowledge of the adaptation efficacy or a low self-efficacy. These barriers are alleviated through the different government interventions, leading to various increases in adoption (colours in Fig. 5). Adoption of drought adaptation measures also varied among the climate scenarios applied (markers in Fig. 5) – as climate change will influence the effectivity of the measures as well as farm households' experience with droughts. Evaluating the effects of climate change and drought risk reduction interventions on the adoption of individual adaptation measures (table B1 in Appendix B), it was evident that the increase in adoption rate of more expensive measures (wells, irrigation infrastructure) is lower than the cheaper options (terraces, mulch) – interventions mainly support the adoption of the latter.

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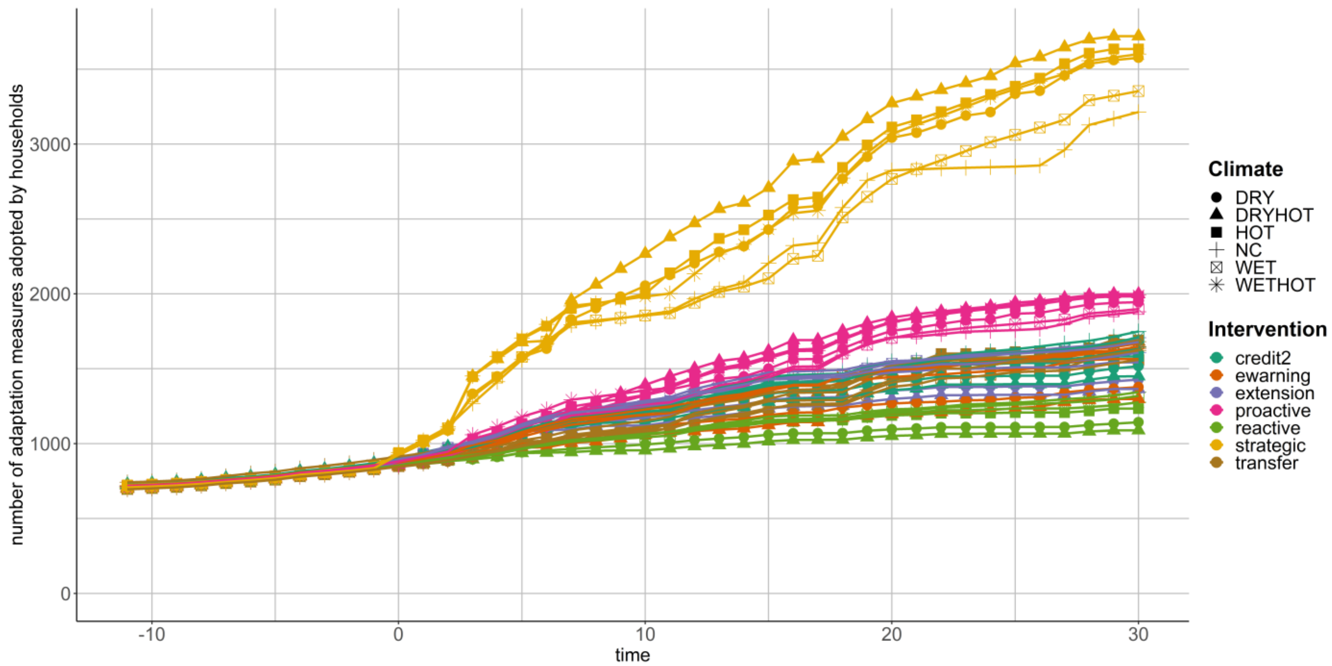

Fig. 5: Total amount of measures adopted per 1000 initialized households. Year 0 initiates climate change scenarios (indicated with different marker shapes), and (non-)governmental drought risk reduction interventions (indicated with different line colours).

Looking into the (non-)governmental intervention scenarios (Fig. 5, table B2 in Appendix B), it is clear that implementing multiple interventions at once resulted in an strong increase in adoption – which can be explained by the alleviation of various adoption barriers at once. Averaging over all adaptation measures, a proactive and strategic intervention plan would increase adaptation respectively 40% and 140% more than under the "no intervention, no climate change" scenario. Both a proactive and strategic (non-)government approach increased the adoption of cheaper measures to close to 100% of the farm households. For the more expensive measures, the proactive scenario showed to be less effective while the strategic scenario reached quite high adoption rates in the more extreme climate scenarios.

When examining the effect of the individual government interventions, affordable credit schemes had the is highest effect on the adoption rate of droughts measures. Furthermore, ex-ante cash transfers (which cannot be seen as large sums of investment money but mere means to keep families food secure) were more effective to increase adoption of the more affordable measures – richer families mostly had already adopted these measures before (non-)governmental interventions were in place. Extended extension service training increased the adoption of less popular measures and decreased the adoption of the popular but not as cost-effective fanya juu terraces. Early Warning Systems surprisingly had more effect in the more wet climate conditions, as the dry-hot scenario had so many drought episodes that risk perception is automatically high while the alert lowers when droughts become more scarce in the less dry scenarios.

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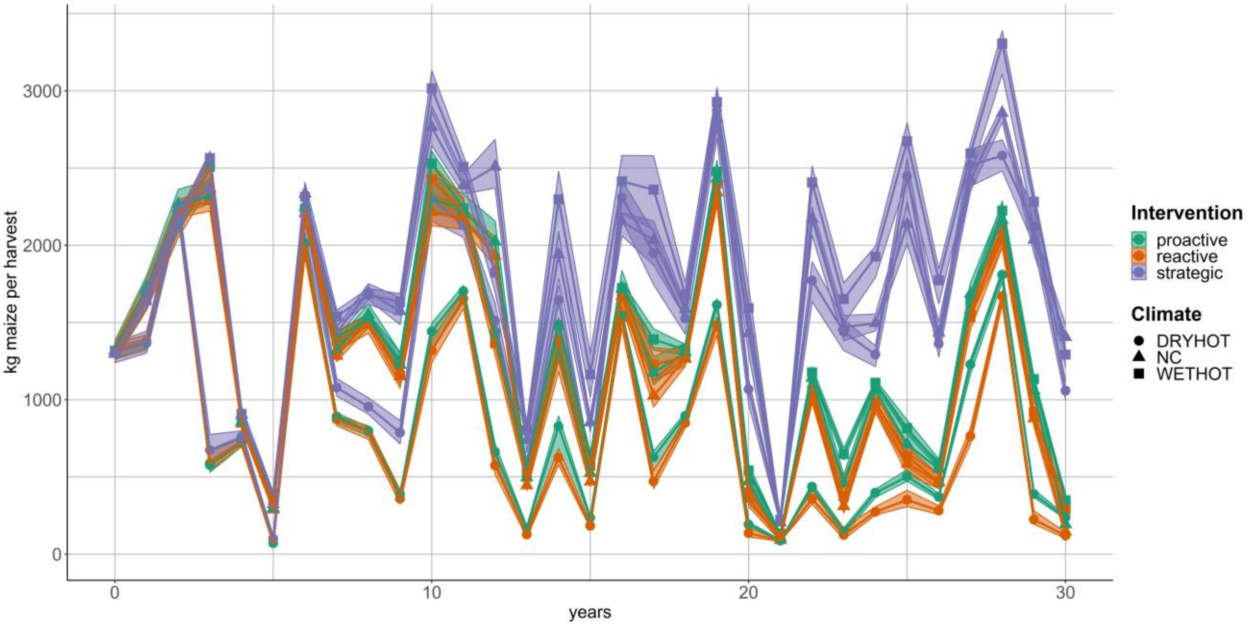

Fig. 6: Household maize harvest (kg/year, sum of two growing seasons) over 30 'scenario years' under different climate change and (non-)governmental intervention scenarios. The shaded area shows the uncertainty range introduced by adding a sensitivity test on the parameterisation of variables describing the adaptive behaviour of the households (i.e. the relative weights of the different determinants of the protection motivation theory).

The adoption of adaptation measures by households influenced their maize yield and thus affected the average and median maize harvest under the different future climates and drought risk reduction interventions (Fig. 6). This is clear comparing the first thirty baseline years with the following thirty scenario years: When no (non-)governmental interventions were in place, average maize yields increased with almost 30% under a wet-hot future and decreased over 25% under a dry-hot climate. Under a strategic government supporting the adoption of adaptation measures, average maize yields increased up to 100% under a wet-hot future and increased with over 60% under dry-hot future conditions. Clearly, an increased uptake of measures did offset a potentially harmful drying climate trend.

Assuming off-farm income to fluctuate randomly but not steadily increasing or decreasing, the changing harvests over time directly affected the poverty rate and the share of households in food insecurity (Fig. 7). Both trends in yield caused by droughts – and thus climate change - or by the adoption of new adaptation measures - potentially instigated by (non-)governmental interventions- , could drive farm household depended on agricultural income in or out of poverty. Running ADOPT with a reactive and no climate change scenario, a slight increase of 5% in poverty levels was visible. Poverty levels increased up to 15% compared to the baseline situation, when a dryer and/or hotter climate scenario was run. A proactive intervention plan reduced poverty with 11% under no climate change, and in the dry-hot climate scenario this combination of improved early warning systems and ex-ante cash transfers lead to reductions of 20-30% compared to the baseline years. However, the strategic government scenario showed the most prominent results, projecting reductions of 45% under no climate change and around 60% under dryer and hotter climate conditions.

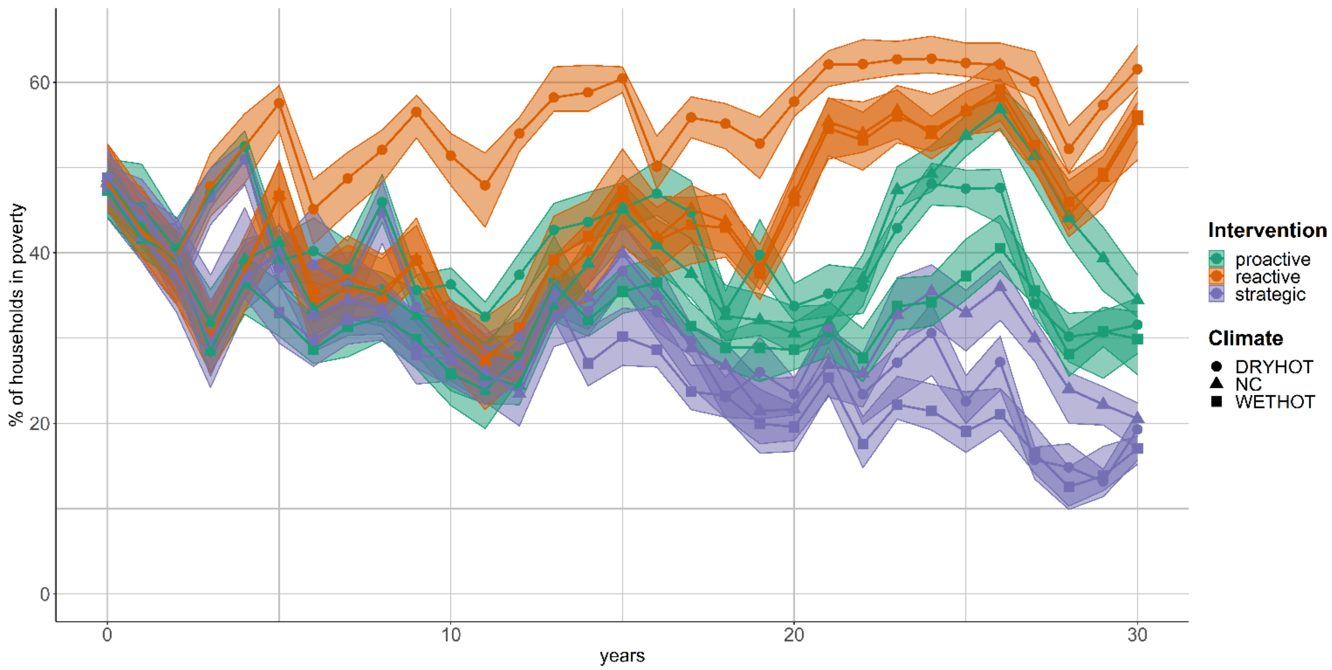

Fig. 7: Share of households in poverty (earning under the 2USD/day income line, under different climate and (non-)governmental intervention scenarios). The shaded area shows the uncertainty range introduced by adding a sensitivity test on the parameterisation of variables describing the adaptive behaviour of the households (i.e. the relative weights of the different determinants of the protection).

Food insecurity is partly caused by a lack of income or assets, but also by the farm market mechanism. Droughts, climate change and adaptation levels influence the availability of maize on this market. Farm households which do not produce enough to be self-sufficient, buy maize on the market if they have the money and if there is maize locally available. Households are assumed to be in food shortage if they have to rely on food aid to fulfil their caloric needs. While on average in the 'no climate change' and 'no (non-)governmental interventions' scenarios, food security rates were predicted to remain stable compared to the baseline period (fig. 8), (non-)governmental interventions and climate change can alter this balance.

Improving extension services or providing ex-ante cash transfers individually showed on average 7.5% more reduction in food insecurity than the reactive government scenario. Improved early warning systems showed on average - over all climate scenarios- an increased reduction of 4.5%. It should be kept in mind that ADOPT does not take into account (illicit) coping activities in the face of droughts such as food stocking or charcoal burning – both of them might reduce the food security threat. Credit schemes at 2%, individually, lead to more than 8% reduction in food insecurity levels as compared to the reactive scenario; but even then on average net food insecurity rates increase due to climate change. A strategic intervention, combining all four interventions, was able to reduce the food insecurity levels over time, even under the dry-hot climate scenario. This scenario was able to counteract the increase in food insecurity, achieving a reduction of households in food insecurity over time with on average 71% compared to the reactive scenario, all climate scenarios considered.

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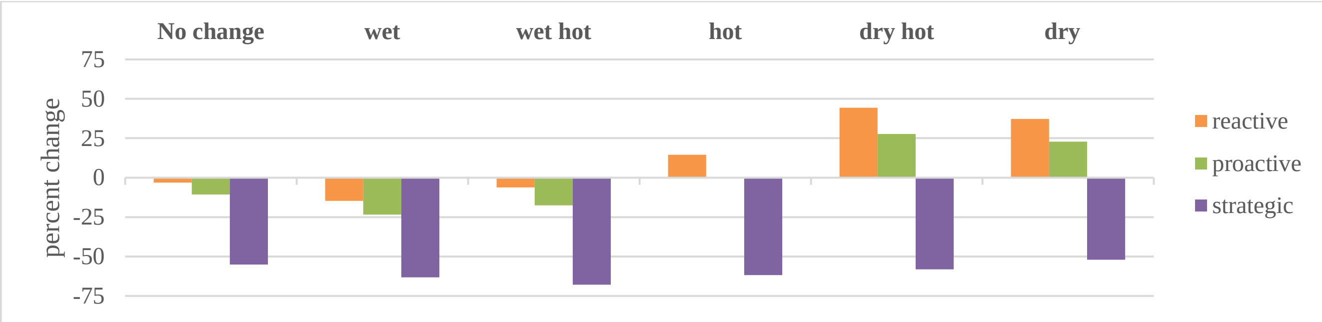

Fig. 8: Percent change in average share of households in food shortage of the 30 years of scenario run, compared to the 30 years of baseline run before "year 0", under different climate and (non-)governmental intervention scenarios. ADOPT model output.

Expressing drought impacts in average annual food aid (in USD, assuming a maize price for shortage markets, as price volatility is taken into account – see ODD+D in Appendix A) can help to evaluate the effect of different climate change scenarios or different (non-)governmental intervention scenarios on the drought risk of the community. Table 2 shows the change in aid needs compared to the no-climate change, no-governmental intervention baseline period (based on the 1980-2010 situation). When assuming no climate change, it seemed that the community is stable, only slightly increasing the share in vulnerable households. More measures were adopted as information is disseminated thought the farmer networks, but those who stay behind will face lower sell prices as markets get more stable and have a harder time accumulating assets. Under wetter conditions, reductions in drought emergency aid did reduce. However, drier, hotter climates had a detrimental effect on the food needs, with more vulnerable people crossing the food shortage threshold.

Under the no climate change scenario, each of the four (non-)governmental interventions did cause a reduction in aid needs, with credit schemes having the largest effect. Under wetter conditions, they also increased the reduction of aid needs compared to the reactive scenario. However, no individual measure, was able to offset the effect of hotter and drier climate conditions. Even under a proactive intervention, there would still be an increase in aid needs under such climate conditions. Only under the strategic intervention scenario, a decrease in aid needs was visible under all possible climate change scenarios.

Table 2: Change in aid needs (%) in 2030-2050 compared to 1980-2010 under different climate and (non-)governmental intervention scenarios. ADOPT model output.

	No change	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive scenario	4%	-29%	-11%	37%	117%	94%
Ex ante cash transfer	-2%	-31%	-20%	24%	92%	76%
Early warning system	-6%	-42%	-24%	25%	109%	86%
Extension services	-20%	-49%	-33%	15%	96%	71%
Credit at 2% rate	-24%	-50%	-33%	10%	86%	62%
Proactive scenario	-15%	-48%	-37%	13%	73%	58%
Strategic scenario	-80%	-81%	-82%	-78%	-68%	-66%

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5. Discussion

5.1 The robustness of drought risk reduction interventions under climate change

Under a reactive strategy ("no intervention") and assuming no climate change, a slow but steady adoption of mulch, fanya juu, shallow well and irrigation practices is estimated. This is a result of an ever increasing information diffusion through the farmer networks and existing extension services, as also found in (Hartwich et al., 2008a; van Duinen et al., 2016a; Villanueva et al., 2016; Wossen et al., 2013). Yet, multiple smallholder households still suffer from the effects of droughts, indicated by the elevated food insecurity rates and poverty rates. While many can break the cycle of drought and subsequent income losses, others are trapped by financial or other barriers and end up in poverty and recurring food insecurity (as also found in e.g. Enfors & Gordon, 2008; Mango et al., 2009; Mosberg & Eriksen, 2015; Sherwood, 2013). Under all climate change scenarios, a lower adoption of adaptation measures compared to the "no climate change" assumption is observed. It shows that the perceived need to adapt, or risk appraisal, is lower under wet conditions and the financial strength to adapt, or coping appraisal, is lower under dry or hot conditions – showing two different barriers to adoption. This link between drought experiences or poverty and adaptation was also found in other studies (e.g. Gebrehiwot & van der Veen, 2015; Holden, 2015; Makoti & Waswa, 2015; Mude et al., 2007; Oluoko-Odingo, 2011; Winsen et al., 2016)

The climate change scenarios portray a different effect on the development of the rural communities. Due to the adaptation choices of the farm households, average maize harvests are estimated to slightly increase under the "no climate change" scenario, and a major increase is estimated under wet and wet-hot conditions where both increased adoption and reduced droughts play a role. Under hot, dry and dry hot conditions, the average household harvests are estimated to decrease (Wamari et al., 2007). Increases in median and mean assets (household wealth) are estimated under the no climate change scenario. Drier climates might lead to decreases in median and mean assets, and hotter climates are estimated to result decreased median but increased average assets of the households. Clearly, the potential future climates very much influence the potential future socio-economic development of smallholder farm households.

Under all (non-)governmental interventions, an increased rate of adoption is observed as compared to the "no intervention" assumption, but the positive effect on household resilience varies. While initially extension services have the largest effect, over time access to credit results in the highest adoption rates and is also estimated to decrease emergency aid the most. While the former is indeed widely recognized as an innovation diffusion tool in different contexts (e.g. (Aker, 2011; Hartwich et al., 2008b; Wossen et al., 2013), the latter is only found to be an effective policy to reduce poverty in Ghana by Wossen and Berger (Wossen & Berger, 2015). The proactive government scenario, "preparing for drought disasters" by improving early warning systems and supporting ex-ante cash transfers, is estimated to level poverty and food security under most climate change scenarios but not under dry conditions. Empirical evidence for the positive effects of ex-ante cash transfers exists (Asfaw et al., 2017; Davis et al., 2016; Pople et al., 2021), and the model estimations might be an underestimation as ADOPT does not account for many preparedness strategies of households such as stocking up food while the price is still low, fallowing land to reduce farm expenses, or searching for other sources of income (Khisa & Oteng, 2014).

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The strategic government scenario "mitigating drought disasters" alleviates multiple barriers to adoption at once, creating a significant increase in adoption. Consequently, this scenario results in a clear growth in resilience of the farm households, shown in more stable income, lower poverty rates and less food insecurity, and is the only scenario estimated to reduce emergency aid under all possible future climates. However, it should be noted that it takes one to two decades to make a significant difference between the reactive stance and strategic intervention plan. In other words: with climate change effects already visible through an increased frequency of drought disasters, and more to be expected within the following 10-20 years – strategic interventions should be taken now in order to be benefit from the increased resilience in time.

5.2 Uncertainties in ADOPT and limitation in investigated measures and interventions

The initial ADOPT model setup was created through interviews with stakeholders, yield data has been validated over the historic period (Wens et al. 2020), and the adaptive behaviour was based on empirical household data (Wens et al.2021). Still, the model output cannot be used as a predicting tool. The past average poverty and food insecurity rates matched observations (Wens 2020), but absolute amounts of emergency aid needs are sensitive to the averages and fluctuations of household assets which proved harder to verify, and poverty and food insecurity depend also on external, food or labour market and other influences which might change towards the future. Besides, the probability of the simulated climate scenarios are unknown, as the East African Climate Paradox (Funk et al., 2021) creates its own set of challenges predicting future weather conditions in the study area. Yet, the relative differences in the risk indicators are informative for the comparison of government interventions under different potential future climates.

Undoubtedly, multiple possible smallholder adaptation measures are omitted in this study. For example, many other agricultural water management measures, agronomic measures, and other climate-smart agricultural water management options exist. Besides, only four different (non-)governmental interventions are evaluated while various other exists. Costs of the government interventions are unknown, making cost-benefit estimates not possible for this study. Also only a small set of potential future climates are evaluated, no full set linked with probabilities is evaluated. While all of these would be possible using the ADOPT model, they require (the collection of) more data for parametrization and calibration. Because results of the future scenario runs cannot be falsified or verified, this study claims not to provide a prediction of the future for south-eastern Kenya. Rather, it showcases the application of ADOPT as a decision support tool while evaluating the robustness of a few, dedicatedly chosen (non-)governmental interventions on adaptation measures under climate scenarios that are deemed to be relevant for the specific area. Future research can use ADOPT to study the differentiated effect of these interventions on different types of households, in order to tailor strategies and target the right beneficiaries of government interventions.

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6. Conclusion

To increase the resilience of smallholder farmers, (non-)governmental interventions might be needed to alleviate barriers to adaptation, increasing farmers' intention to adopt drought adaptation measures. However, to which extent these interventions will steer farmers' adaptive behaviour, hence how effective they are in reducing the farm household drought risk, often remains unknown. The agent-based drought risk model ADOPT is used to evaluate the effectivity and robustness of various (non-)governmental interventions under different climate change scenarios. ADOPT captures the feedbacks between agricultural water management decisions by smallholder farmers and seasonal weather conditions, and explicitly models adoption constraints and social interactions among farmers.

In this study, ADOPT is applied to evaluate the effect of potential future scenarios regarding climate change and (non-)governmental interventions on agricultural drought risk in south-eastern Kenya. The smallholder farmers in this region face barriers to adopt drought adaptation measures such as mulching, fanya juu terraces, shallow wells, and drip irrigation, to stabilize production and income. ADOPT simulates their adaptive behaviour, influenced by drought occurrences under changing climate conditions, and by (non-)government drought risk reduction interventions such as the introduction of ex-ante cash transfers, affordable credit schemes, improved early warning systems and tailored extension services, which results in a changing individual and community drought risk over time.

We show that all investigated interventions have a positive effect on the uptake of adaptation measures, reducing the drought-related shocks in maize production and increasing the average yields, thus reducing the need for external food aid. Extension services increase the adoption of low-cost, unknown drought adaptation measures while credit schemes are useful for cost-effective but expensive drought adaptation measures. Ex-ante cash transfers allow the least endowed households to adopt low-cost popular drought adaptation measures. Early warning systems are more effective in climate scenarios with less frequent drought if used as a tool to create awareness and risk perception.

An increased uptake of adaptation measures by smallholder farmers can offset a potentially harmful drying climate trend, but this study shows that alleviating only one barrier to adoption has a limited result on the resilience of the farm households. Only by combining all four interventions, simultaneously increasing risk perception, reducing investment costs, and elevating self-efficacy, nonlinear synergies arise resulting in a strong increase in the adoption of measures. Under such strategic government approach, ADOPT estimates significantly reduced food insecurity, decreased poverty levels, and drastically lower drought emergency aid needs after 10 to 20 years, under all investigated climate change scenarios.

This study proves that, in order to achieve the current targets of the Sendai Framework for Disaster Risk, which aims at building a culture of resilience and to a achieve Sustainable Development Goals "zero hunger", "sustainable water management" and "climate resilience", a holistic approach combining multiple interventions is needed now to build a sustainable future for smallholder farmers in Kenya's drylands. Besides, it provides evidence that agent-based models such as ADOPT can serve as decision support tools to tailor drought risk reduction interventions under uncertain future climate conditions.

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Appendices

Appendix A: Description of the ADOPT model following the ODD+D protocol for ABM ((Laatabi et al., 2018; Müller et al., 2013)**):**

Outline		ADOPT Model description
Overview	I.i Purpose	*What is the purpose of the study?* The purpose of this study is evaluating the effect of possible climate change and (non-)governmental policies on drought risk of smallholder farmers. The ADOPT model is capable of simulating the farm conditions and adaptation decisions of these farm households, and designed to include different climate and policy scenarios and their effect on the livelihoods of these last. *:* The model is designed to disentangle complex adaptive behaviour in an agricultural drought risk context. The multi-disciplinary modelling approach is rooted in quantitative socio-hydrology framework', where the human system both influences and adapts to the changing physical agricultural drought environment, and adopts an agent-based approach to deal with heterogeneity in adaptive behaviour of smallholder households. Understanding the two-way feedback between households' adaptation decisions and maize yield losses over time will help optimize future drought impact estimations and allow for the testing of drought management policies
		For whom is the model designed? The adopt model can allow scientists to increase understanding of the socio-hydrological reality of drought risk and drought adaptation, while it can help decision makers to design drought policies that target the right farm household and evaluate their effect on their drought vulnerability.
	I.ii Entities, state variables, and scales	*What kinds of entities are in the model?* The agents in ADOPT are individual farm households that have a farm of varying size and potentially an off farm income source. Farm households are connected to their neighbours in a network setting, ADOPT runs on the farm scale, modelling yield per household farm.
		By what attributes are these entities characterized? Farm households have, other than a farm with a specific farm size, a family size; a household head (male/female), a stock of assets, income sources and farm experience. Household heads have a memory regarding past drought impacts, have a perception about their own capacity and in varying degrees, have information about potential adaptation measures. Farms, belonging to households, are assumed to be producing maize under certain fixed and changing water management conditions. They are exposed to daily weather conditions and produce maize harvest twice a year.
		What are the exogenous factors of the model? Two exogenous factors influence the farm household systems: climate change and (non-)governmental policies. The first alter the frequency of droughts – potential failed crop yields – while the latter affects the knowledge, access to credit and risk perception of households who are recipient of the policies.
		How is space included in the model? As the space is spatially implicit, all farm household farms receive the same amount of rain and sun, differentiating only in their size an management applied.
		What are the temporal resolution and extent of the model? One time step of ADOPT represents one year. The crop model part runs on a daily basis, producing seasonal maize crop yield, but decisions by the farm households to eventually adopt new adaptation measures are only made in the long dry season, once every year. Each year, the poverty status, food security situation and potential food aid needs of all farm households are evaluated. The model runs 30 years historic baseline and 30 scenario years.

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	I.iii Process overview and scheduling	*What entity does what, and in what order?* The farm income (harvest) – whether or not affected by a drought – influences the annual income of the farm household; the household head decides based on her/his memory of past droughts, on the knowledge through her/his network and its own capacity, whether or not he/she want and is able to adopt a new drought adaptation measure. The decision to adopt a new measures changes the farm management of the next years, hence crop yields for the following seasons.
Design Concepts	II.i Theoretical and Empirical Background	*Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) ?* The crop water model assumes that, with knowing the soil and crop characteristics and the farm management practices, crop yield can be predicted based on the weather conditions. The FAO crop water model, simulates the daily growth of biomass / roots of crops
		On what assumptions is/are the agents' decision model(s) based? The PROTECTION MOTIVATION THEORY has been applied to predict and understand protective behaviour (Rogers 1983). PMT consists of two underlying cognitive mediating processes that cause individuals to adopt protective behaviors when faced with a hazard (Rogers 1983; Rogers and Prentice-Dunn 1997). These are the Risk-appraisal process forming a risk perception and the coping-appraisal process forming a perception of the adaptation-efficacy.
		Why is a/are certain decision model(s) chosen? Analysis of the past and intended behaviour of farm households in the region (Wens 2021?) provided support for the choice of theory, but also showed the need to include network influencing risk perception and capacity of the households. Besides helping to parameterize the model, it also helped to calibrate the influence of the different factors affecting the decision making process of the farm household. Showing the effect of different assumptions about decision making in Wens et al 2020, and with empiric evidence on the adaptive behaviour (Wens 2021), the decision rules in ADOPT are assumed be a good enough representation of the processes that matters in the decision making on drought adaptation.
		If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from? ADOPT is calibrated with data from existing longitudinal household surveys (TEGEMEO 2000 2004 2007 2010) and from a fuzzy cognitive map of key informants, and a semi-structured household questionnaire among 260 smallholder farmers (Wens 2018, 2019, 2021)

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	II.ii Individual Decision Making	*What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included? What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria? How do agents make their decisions? Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?* In ADOPT, decision making is coded assuming complex behaviour of individual farm households. Factors influencing the adoption of drought adaptation measures can generally be categorized into extrinsic factors and intrinsic factors. Extrinsic factors include the social and natural environment in which households exists. This steers a households' perception of the drought risks they face (Risk Appraisal). For example, experiences of historic droughts affects individuals' evaluation of drought risk leading to a biased drought risk judgement (e.g. Singh and Chudasama 2017; Keshavarz & Karami 2014). Generally, more vulnerable households have greater risk perceptions (van Duinen et al. 2016). Besides, access to extension services (field demonstrations, farmer trainings) - used as primary source of information by 30%-, and other sources of information sharing (i.e. through the social network (18%) or NGOs (10%) can have profound effect on whether or not individuals take proactive action (Kitinya et al., 2012; Shikuku, 2017; Haer et al. 2016). Also age, gender and education can play a role (Burton 2014) Knowing the risk and knowing how to or being able to respond to the risk are not the same, as one should believe a measure will be effective, be convinced that one has the ability to implement the measure and be able to pay reasonable costs (Van duinen). Financial or knowledge constraints may limit economic rational decisions. Also the perceived ability to do something (Coping Appraisal) influences the decision making process (Esner 2012, Eiser 2012). This coping appraisal can be subject to intrinsic factors such as education level, sources of income, farm size, family size, gender, confidence and beliefs, risk-aversion, and age (Shikuku, 2017; Okumu, 2013; Eisner 2012, Van duinen, Dang et al 2014; Zhang et al 2019). In order to understand the observed adaptive behaviour of Kenya's smallholder households, it is critical to incorporate such social-economic factors in the decision-making framework of drought adaptation models (Van duinen et al 2015; Keshavarz & Karami 2014; SRezael salmani 2017; ingh and Chudasama 2017; O'Brien et al., 2006; Maddison, 2007; Adger et al., 2009; Jones and Boyd, 2011; lalani et al 2016; Maddison 2007; Gbet- ibouo 2009; Deressa et al. 2011; Mandleni and Anim 2011; Wheeler et al. 2013; Gebrehiwot van der veen, Keshavarsz 2016).
	II.iii Learning	*Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?* Often, initial decisions, made by a few, can grow into large collective interventions, either through government incentive or social networks (Willy et al 2013, Ertsen et al.,2013; Holman et al., 2018). In ADOPT, households interact with their neighbours through traditional forms of labour exchange, cooperatives, pioneer households' and family ties; shaping risk awareness and response attitude (Okumu 2013, Shikuku 2017, Nkatha 2017). Such group membership can enhance social learning and knowledge spill over which influences people's adaptation intention and choice of specific measures (Tongruksawattana 2014; Below et al 2010). In the model, this translates to individual risk perception changing in the direction of the mean risk perception within individuals' social network (Haer?). Besides, households that do not regularly receive extension services, are limited to only implement measures that more than 2 of their neighbours have installed

	II.iv Individual Sensing	*What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?* Following the socio-hydrologic setup of the model, households with bounded rational behaviour are embedded in and interact with their social and natural environment. Changes in rainfall patterns during growing season will change households' risk perception; drought memory will influence the adaptive behaviour of these households.
		What state variables of which other individuals can an individual perceive? Households are aware of their assets, past yields, income sources and their stability, and household food needs Households know their own but also their neighbours current yields and management practices
		What is the spatial scale of sensing? Individual sensing happens on household level, but the model also produces overall statistics; like the average or median yield, the percentage of households in poverty or the total amount of food needed to cover all shortages.
		Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables? Sensing happens locally and households have a simulated "contact" with the farmers in their network to exchange info on risk and yields.
	II.v Individual Prediction	*Which data uses the agent to predict future conditions?* By extrapolating from historic yield experiences, farmers have an expected yield every year.
		What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? Households receiving extension services have the capacity to predict the average yield gain of adopting a new adaptation measure, which will influence their coping appraisal.
		Might agents be erroneous in the prediction process, and how is it implemented? Households without this access to training will predict the yield gain based on the extra yield of their neighbours with the considered adaptation measure
	II.vi Interaction	*Are interactions among agents and entities assumed as direct or indirect?* Smallholder households learn from the other households in their social network about the implementation and benefits of drought adaptation measure through pioneer households' and family ties (Below et al 2010; Shikuku 2017). In ADOPT, social interaction is explicitly modelled. Interventions with neighbours shape risk perception – the individual perception moves in the direction of the social network average – and also shape response attitude – households with no access to extension can only adopt measures already implemented by neighbours
		On what do the interactions depend? Spatial distance (neighbourhood) is the main driver for networks; it is assumed a farmer cannot have more than 30 other farmers in her/his close, influential network, and it is assumed that s(he) would not walk more than 5km to reach persons in her/his network
	II.vii Collectives	*Do the individuals form or belong to aggregations that affect, and are affected by, the individuals?* Households are either more self-oriented, discussing matter with 10 neighbours, or group-oriented, sharing knowledge within a group / collective of 30 neighbouring households. Group membership (traditional forms of labour exchange, cooperatives, …) can enhance social learning and knowledge spill over; Often, initial decisions, made by a few, can grow into large collective interventions, either through government incentive or social networks (Ertsen et al.,2013; Holman et al., 2018).
		How are collectives represented? Group membership and network size are set at the initialization phase and do not change over time

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	II.viii Heterogeneity	Are the agents heterogeneous? Household agents are heterogeneous in terms of state variables (i.e. farm size, household size, assets), and agent categorization (certain-knowledgeable or uncertain) (Shikuku 2017, Asfaw et al 2012
		Are the agents heterogeneous in their decision-making? Households can be inclined to adopt new technology or can be conservative (attitude-towards-change). Okumu (2013), Shikuku (2017) – among others - found that state variables such as age, gender, education of the household head and the household size have significant effects on this risk- attitude.
	II.ix Stochasticity II.x Observation	*What processes (including initialization) are modeled by assuming they are random or partly random?* During the initialization, the household attribute values are derived stochastically within the uncertainty range values based on the survey data. For every subsequent time loop of the simulation, a random number between 0-1 is drawn for each household; if this is lower than their adaptation intention (also between 0-1) and the household is able to pay for the measure; then the household adopts it. This way, we account for non-included factors introducing uncertainty in adaptive behaviour such as beliefs, physical health, ambitiousness etc. of the households. Moreover, also a stochastic perturbation is added to the Maize yield per farm as calculated through Aquacrop – this to include effects of pests and diseases on the income and food security of farming households.
Details	II.i Implementation Details	*How has the model been implemented?* The model is coded in R, which is able to link the two sub models in Netlogo (the adaptive behaviour sub model) and Matlab (AquacropOS).
	III.ii Initialization	*What is the initial state of the model world, i.e. at time t=0 of a simulation run?* At the initial stage, households and their characteristics are randomly created based on the mean and standard deviation derived from the household dataset.
		Is initialization always the same, or is it allowed to vary among simulations? The weather situation from 1980-2010 is used as initialization phase where households initialize their risk perception and coping appraisal in the.
		Are the initial values chosen arbitrarily or based on data? The initial setup values are based on reports / surveys from the area (Tegemeo Dataset 2000,2004,2007,2010, and own surveys from 2019 (250 farmers)). The socio-economic household characteristics are summarized in table A, while the bio-physical field characteristics are summarized in table B

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	III.iii Input Data	*Does the model use input from external sources such as data files or other models to represent processes that change over time?* The setup of the model is a result of participatory concept mapping with researchers and students of SEKU University, technical advisors of Kitui County department of water, agriculture, livestock and fishing, experts from SASOL foundation and 5 pilot households that have example farms for agricultural extension. The input data for the decision model was obtained from a survey on agricultural drought risk to smallholders in the case study area (Wens, 2019). Survey data includes a short questionnaire among employees of the Kenyan national disaster coordination units (n=10), semi-structured expert interviews (n=8) with NGOs, governmental water authorities and pioneer farmers in the Kitui district in Kenya, and an in-depth questionnaire among 250 smallholder farmers in the central Kitui. Extra information is derived from a household surveys in 2000, 2004, 2007 and 2010, conducted by the Tegemeo Agricultural Policy Research Analysis (TARAA) Project of the Tegemeo Institute. The project collects comprehensive information on rural households including, among others, demographic information, information on agricultural practices, business and informal labour practices, decision making, household assets and consumption in different counties in Kenya. Besides, the model initialization draws heavily from reports of CIAT (Climate-Smart Agriculture in Kenya), FAO (The economic lives of smallholder households), IFPRI and the government of Kenya (County integrated development plans), CCAFS (Baseline Survey Indicators for Makueni/Wote, Kenya.), and from research (characterization of Maize producing households in Machakos and Makueni Districts) of Muhamad et al. (2010).
	III.iv Submodels	*What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?* The FAO crop-water model Aquacrop OS (coded in Matlab© by Tim Foster (Foster et al.)) calculates seasonal crop production, based on hydro-climatologic conditions provided by the climate data and based on the agricultural management of the households. The agent-based model in which farming households decide on their drought adaptation measures, is coded in Netlogo®, a language specialized in ABMs.
		How were submodels designed or chosen, and how were they parameterized and then tested? AquacropOS was applied following Ngetich and Omyo, who both analyzed and approved the functioning of this model to simulate maize yield under different climates in Kenya.

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Table A: Initialisation parameters for farm households in ADOPT

Parameter	Explanation of initialization parameters for farm households	Value
Age	Age of the household head (based on Wens 2019)	42 +- 9
Edu	Years of education of the household head (based on Wens 2019)	6 +- 3
Sex	Gender of the household head (male 1, female 0)	0.66
HH-size	Family size of the households (people living under same roof) (Wens 2019)	6 +- 2.5
Assets	Household financial assets (USD) that can be spend (based on IFPRI 2012)	80% < 100
Farm-size	Size of the farm (in hectare) used for planting crops (Wens 2019)	0.7 +- 0.6
Off-farm	Income from activities not on the own farm in USD (Wens 2019)	1200 +- 500
Foodneeds	Kilogram of maize to fulfil daily caloric intake needs, per adult	125
Exp-farm	Farm expenditures made by the household (USD/hectare/year) (Wens 2019)	118 +- 146
Exp-food	Food expenditures made by the household (USD/year) (Wens 2019)	567 +- 655
Exp-nonf	Other expenditures made by the household (USD/year) (Wens 2019)	446 +- 500

Table B: Initialisation parameters for AQUACROPOS in ADOPT

Value	Explanation of calibration parameters for AquacropOSv6.0 maize
60 / 80	Curve number value under fanya juu bunds or under absence of such bunds
06	Bund height (m)
50	Area of surface covered by mulches (50%)
0.5	Soil evaporation adjustment factor due to effect of mulches
SMbased	Irrigation method
7 / 3	Interval irrigation in days under manual / automated irrigation
40	Soil moisture target (% of TAW below which irrigation is triggered)
12	Maximum irrigation depth (mm/day)
50 / 75	Application efficiency under manual / automated irrigation
50	Soil surface wetted by irrigation (%)

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Table C: Crop parameters for maize AQUACROPOS in ADOPT

Value	**Crop parameters for AquaCropOS**
3	: Crop Type (1 = Leafy vegetable, 2 = Root/tuber, 3 = Fruit/grain)
1	: Planting method (0 = Transplanted, 1 = Sown)
1	: Calendar Type (1 = Calendar days, 2 = Growing degree days)
0	: Convert calendar to GDD mode if inputs are given in calendar days (0 = No; 1 = Yes)
16/03	: Planting Date (dd/mm)
31/08	: Latest Harvest Date (dd/mm)
5	: Growing degree/Calendar days from sowing to emergence/transplant recovery
40	: Growing degree/Calendar days from sowing to maximum rooting
80	: Growing degree/Calendar days from sowing to senescence
90	: Growing degree/Cale ndar days from sowing to maturity
40	: Growing degree/Calendar days from sowing to start of yield formation
5	: Duration of flowering in growing degree/calendar days (-999 for non-fruit/grain crops)
65	: Duration of yield formation in growing degree/calendar days
3	: Growing degree day calculation method
8	: Base temperature (degC) below which growth does not progress
30	: Upper temperature (degC) above which crop development no longer increases
1	: Pollination affected by heat stress (0 = No, 1 = Yes)
35	: Maximum air temperature (degC) above which pollination begins to fail
40	: Maximum air temperature (degC) at which pollination completely fails
1	: Pollination affected by cold stress (0 = No, 1 = Yes)
10	: Minimum air temperature (degC) below which pollination begins to fail
5	: Minimum air temperature (degC) at which pollination completely fails
1	: Transpiration affected by cold temperature stress (0 = No, 1 = Yes)
12	: Minimum growing degree days (degC/day) required for full crop transpiration potential
0	: Growing degree days (degC/day) at which no crop transpiration occurs
0.3	: Minimum effective rooting depth (m)
0.8	: Maximum rooting depth (m)
1.3	: Shape factor describing root expansion
0.0105	: Maximum root water extraction at top of the root zone (m3/m3/day)
0.0026	: Maximum root water extraction at the bottom of the root zone (m3/m3/day)
6.5	: Soil surface area (cm2) covered by an individual seedling at 90% emergence
37000	: Number of plants per hectare
0.89	: Maximum canopy cover (fraction of soil cover)
0.1169	: Canopy decline coefficient (fraction per GDD/calendar day)
0.2213	: Canopy growth coefficient (fraction per GDD)
1.05	: Crop coefficient when canopy growth is complete but prior to senescence
0.3	: Decline of crop coefficient due to ageing (%/day)
33.7	: Water productivity normalized for ET0 and C02 (g/m2)
100	: Adjustment of water productivity in yield formation stage (% of WP)

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50	: Crop performance under elevated atmospheric CO2 concentration (%)
0.48	: Reference harvest index
0	: Possible increase of harvest index due to water stress before flowering (%)
7	: Coefficient describing positive impact on harvest index of restricted vegetative growth during yield formation
3	: Coefficient describing negative impact on harvest index of stomatal closure during yield formation
15	: Maximum allowable increase of harvest index above reference value
1	: Crop Determinancy (0 = Indeterminant, 1 = Determinant)
50	: Excess of potential fruits
0.02	: Upper soil water depletion threshold for water stress effects on affect canopy expansion
0.20	: Upper soil water depletion threshold for water stress effects on canopy stomatal control
0.69	: Upper soil water depletion threshold for water stress effects on canopy senescence
0.80	: Upper soil water depletion threshold for water stress effects on canopy pollination
0.35	: Lower soil water depletion threshold for water stress effects on canopy expansion
1	: Lower soil water depletion threshold for water stress effects on canopy stomatal control
1	: Lower soil water depletion threshold for water stress effects on canopy senescence
1	: Lower soil water depletion threshold for water stress effects on canopy pollination
1	: Shape factor describing water stress effects on canopy expansion
2.9	: Shape factor describing water stress effects on stomatal control
6	: Shape factor describing water stress effects on canopy senescence
2.7	: Shape factor describing water stress effects on pollination

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Appendix B: Adoption rates of adaptation measures

485 **Table B1 Adoption ratio (in share of population) at run year 30 under different climate and intervention scenarios. Note that the model showed an adoption rate of 25% for mulch, 70% for fanya juu, 9% for well and X% for irrigation at run year 0 (start of climate change and policy scenarios) .**

Mulch	**NoChange**	**Wet**	**Wet Hot**	**Hot**	**Dry Hot**	**Dry**
Reactive	50.2%	47.8%	45.6%	42.1%	35.9%	38.5%
Proactive	83.8%	83.6%	89.4%	90.1%	90.7%	88.1%
Strategic	100%	100%	100%	100%	100%	100%
Fanyajuu	NoChange	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive	71.1%	70.9%	69.1%	68.8%	60.7%	63.3%
Proactive	87.2%	88.1%	90.7%	90.9%	91.9%	90.1%
Strategic	93.7%	93.5%	94.7%	94.8%	95.1%	94.9%
Well	NoChange	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive	9.4%	9.6%	9.4%	9.2%	9.1%	9.0%
Proactive	11.7%	12.7%	13.4%	12.0%	12.1%	11.4%
Strategic	79.4%	82.6%	92.1%	92.9%	95.0%	91.1%
Irrigation	NoChange	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive	3.7%	3.7%	3.5%	3.4%	3.3%	3.4%
Proactive	5.2%	5.6%	5.6%	5.3%	5.2%	4.8%
Strategic	48.7%	59.6%	73.3%	75.8%	82.0%	71.8%

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Table B1 Difference in adoption RATIO (in share of population) under different climate and intervention scenarios compared to the reactive government scenario under no climate change (the BAU scenario).

mulch	**NoChange**	**Wet**	**Wet Hot**	**Hot**	**Dry Hot**	**Dry**
Reactive	0	-2.5%	-4.6%	-8.1%	-14.3%	-11.6%
Proactive	33.7%	33.4%	39.3%	39.9%	40.5%	38.0%
Strategic	49.4%	49.4%	49.8%	49.8%	49.8%	49.8%
EWS	18.0%	19.7%	18.8%	13.5%	-4.5%	1.2%
transfer	23.2%	14.4	19.6%	24.6%	23.8%	18.4%
Credit2	19.5%	16.6%	14.7%	8.5%	5.4%	9.1%
training	30.1%	27.6%	24.9%	20.4%	10.8%	15.1%

Fanya Juu	NC	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive	0%	-0.2%	-2%	-2.3%	-10.3%	-7.7%
Proactive	16.2%	17.0%	19.6%	19.8%	20.8%	19.1%
Strategic	22.6%	22.4%	23.6%	23.8%	24.1%	23.8%
EWS	8.2%	9.2%	8.5%	6.0%	-0.2%	1.3%
transfer	9.0%	5.9%	6.9%	10.3%	10.1%	8.4%
Credit2	8.0%	7.3%	5.1%	6.0%	-0.1%	1.5%
training	-1.7%	-2.9%	-5.1%	-5.5%	-11.2%	-9.9%

Well	NC	Wet	Wet Hot	Hot	Dry Hot	Dry
Reactive	0%	0.2%	-0.1%	-0.3%	-0.4%	-0.4%
Proactive	2.4%	3.2%	3.9%	2.6%	2.7%	2.0%
Strategic	69.9%	73.2%	82.7%	83.4%	85.5%	81.6%
EWS	1.7%	2.%	1.4%	1.1%	-0.4%	0.2%
transfer	10.%	1.0%	1.1%	0.2%	0.4%	0.2%
Credit2	9.4%	9.1%	7.4%	6.9%	4.2%	5.1%
training	5.2%	5.5%	4.4%	3.2%	1.5%	1.9%

Irrigation	NC	Wet	Wet Hot	Hot	DRY	Dry Hot
Reactive	0%	0%	-0.1%	-0.3%	-0.4%	-0.3%
Proactive	1.5%	1.9%	1.9%	1.6%	1.5%	1.2%
Strategic	45.1%	56.0%	69.6%	72.1%	78.3%	68.1%
EWS	1.3%	1.6%	1.6%	1.4%	0.5%	0.7%
transfer	0.6%	0.3%	0.1%	-0.2%	-0.4%	-0.4%
Credit2	3.7%	3.7%	2.8%	2.4%	1.2%	1.7%
training	2.8%	3.3%	2.2%	1.7%	0.9%	1.3%

% change tov 1343 adopted measures under NC reactive						
Total	NC	Wet	Wet Hot	Hot	DRY	Dry Hot
Reactive	0%	-1.8%	-5.0%	-8.2%	-18.9%	-15.0%
Proactive	40.0%	41.2%	48.2%	47.6%	48.8%	44.8%
Strategic	139.2%	149.6%	167.9%	170.5%	176.9%	166 2%
EWS	21.7%	24.2%	22.6%	16.4%	-3.4%	2.5%
transfer	25.1%	16.1%	20.7%	25.9%	25.2%	19.8%
Credit2	30.2%	27.3%	22.3%	17.7%	7.9%	12.9%
training	27.0%	24.9%	09.7%	14.8%	1.6%	6.2%

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Author contribution

M. W. took lead in model development, scenario development and writing the manuscript. T.V. assisted model development, A.v.L. assisted with manuscript writing and both contributed to the scenario development. J.A. was at the basis of the creative process of model setup, development and model application and contributed to the manuscript writing.

Competing interests

The authors declare that they have no conflict of interest.

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