

1 Education, financial aid and awareness can reduce smallholder 2 farmers' vulnerability to drought under climate change

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7 **Abstract.** Analyses of future agricultural drought impacts require a multidisciplinary approach in which both
8 human and environmental dynamics are studied. In this study, we used the socio-hydrologic, agent-based drought
9 risk adaptation model ADOPT. This model simulates the decisions of smallholder farmers regarding on-farm
10 drought adaptation measures, and the resulting dynamics in household vulnerability and drought impact over
11 time. We applied ADOPT to assess the effect of four top-down disaster risk reduction interventions on
12 smallholder farmers' drought risk in the Kenyan drylands: The robustness of additional extension services, ex-
13 ante rather than ex-post cash transfers, improved early warnings and lowered credit rates was evaluated under
14 different climate change scenarios.

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

23

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

26 **1 Introduction**

27 Droughts, defined as below-normal meteorological or hydrological conditions, are a pressing threat to the food
28 production in the drylands of Sub-Saharan Africa (Brown et al., 2011; Cervigni & Morris, 2016; UNDP et al.,
29 2009). Over the last decades, increasing temperatures and erratic or inadequate rainfall have already intensified
30 drought disasters (Khisa, 2017). Climate change, population growth and socio-economic development will lead
31 to additional pressures on water resources (Erenstein, Kassie, & Mwangi, 2011; Kitonyo et al., 2013). In Kenya,
32 three quarters of the population depend on smallholder rain-fed agricultural production and nearly half of the
33 population is annually exposed to recurring drought disasters causing income insecurity, malnutrition and health
34 issues (Alessandro et al., 2015; Khisa, 2018; Mutunga et al., 2017; Rudari et al., 2019; UNDP, 2012). Reducing
35 drought risk is imperative to enhance the resilience of the agriculture sector, to protect the livelihoods of the rural
36 population, and to avoid food insecurity and famine in Kenya's drylands (Khisa, 2017; Shikuku et al., 2017).

37 Drought risk models are important tools to inform policy makers about **the effectiveness** of adaptation policies
38 and enable the design of customized drought adaptation strategies under different future climate scenarios (Carrao
39 et al., 2016; Stefano et al., 2015). Traditionally, such models express disaster risk as the product of hazard,
40 exposure and vulnerability, and are based on historical risk data. Recent disaster risk models have dealt with
41 climate change adaptation in a two-stage framework; first describing a few scenarios regarding adaptation choices
42 of representative households, then estimating the impacts of adaptation on (future-) welfare while assuming
43 climate change scenarios (di Falco, 2014). However, most existing research does not account for more complex
44 dynamics in adaptation and vulnerability (Conway et al., 2019), for the heterogeneity in human adaptive
45 behaviour (Aerts et al. 2018) or for the feedback between risk dynamics and adaptive behaviour dynamics (Di
46 Baldassarre et al., 2017). Though, these are the aspects that determine, for a large part, the actual risk (Eiser et
47 al., 2012).

48 It appears that farmers often act boundedly rational towards drought adaptation rather than economically rational:
49 their economic rationality is bounded in terms of cognitive capability, information available, perceptions,
50 heuristics and biases (Schrieks et al., 2021; Wens et al., 2021). To account for such individual adaptive behaviour
51 in drought risk assessments, an agent-based modelling technique can be applied (Berger & Troost, 2014; Blair &
52 Buytaert, 2016; Filatova et al., 2013; Kelly et al., 2013; Matthews et al., 2007; Smajgl et al., 2011; Smajgl &
53 Barreteau, 2017). Agent-based models allow explicit simulation of the bottom-up individual human adaptation
54 decisions and capture the macro-scale consequences that emerge from the interactions between individual agents
55 and their environments. Combining risk models with an agent-based approach is thus a promising way to analyse
56 drought risk, and the evolution of it through time, in a more realistic way (Wens et al., 2019).

57 Here we present how an agent-based drought risk adaptation model, ADOPT (designed in Wens et al 2020), can
58 increase our understanding of the effect of drought policies on community-scale drought risk for smallholder
59 farmers in Kenya's drylands.. The design of ADOPT as an agent-based drought risk adaptation model is described
60 in Wens et al., 2020. Moreover, Wens et al. (2021) detail the empirical data on past adaptive behaviour (used to
61 calibrate the model), as well as empirical data on adaptation intentions that can be used to compare with the model
62 outputs.

63 In this study, we apply the ADOPT model, to test the variation in household drought risk under different drought
64 management policies: (i) a reactive government only providing emergency aid, (ii) a pro-active government,
65 which provides sufficient drought early warnings and ex-ante cash transfer in the face of droughts , and (iii) a
66 prospective government that, in addition to early warnings and ex-ante transfers, subsidises adaptation credit
67 schemes and provides regular drought adaptation extension services to farmers. In addition, ADOPT is used to
68 evaluate the robustness of these policies under different climate change scenarios. We acknowledge that ADOPT
69 should be subject to additional validation steps in order to more accurately and precisely predict future drought
70 risk. Yet, in this study we elaborate the potential of this proof-of-concept model by showcasing the trends in
71 drought risk under risk reduction interventions and climate change for a case study in semi-arid Kenya.

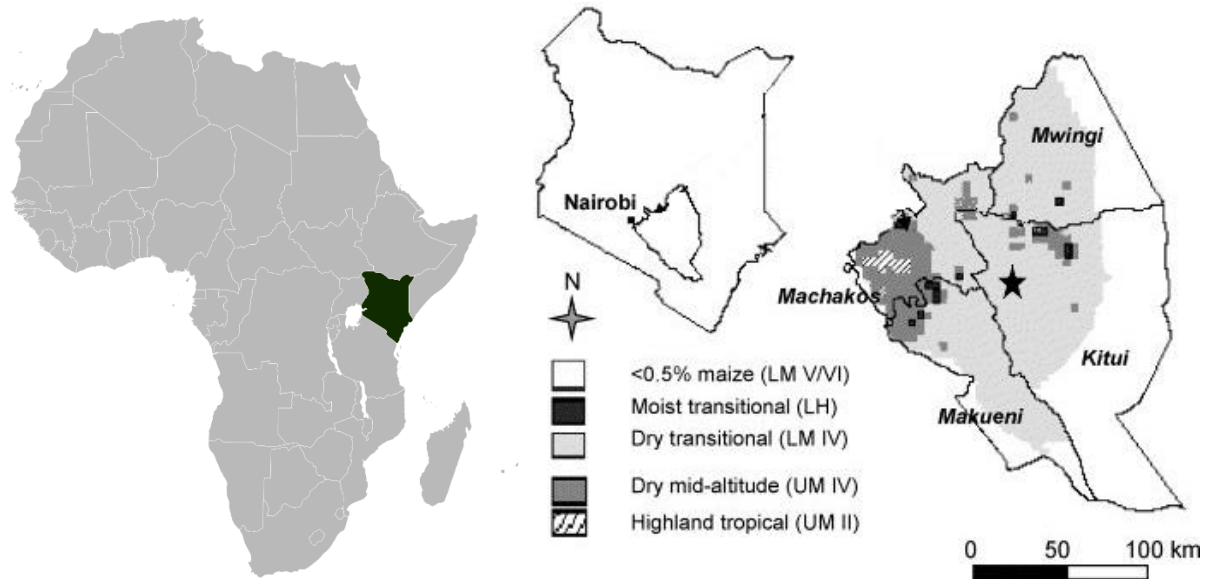
72 **2 Case study description**

73 The ADOPT model has been applied to the context of smallholder maize production in the dryland communities
74 in the areas Kitui, Makueni and Machakos in south-eastern Kenya (fig. 1). This semi-arid to sub-humid region
75 is drought-prone, being hit by drought disasters in 1983/84, 1991/92, 1995/96, 1998/2000, 2004/2005, and 2008-
76 11, 2014-2018 (data from Em-Dat and DesInventar). The majority of the population in this dry transitional
77 farming zone is directly or indirectly employed through agriculture. However, technology adoption and
78 production level remain rather low, making the region very vulnerable to droughts and climate change (Khisia &
79 Oteng, 2014; Mutunga et al., 2017).

80 In Kenya, 75% of the country's maize is produced by smallholder farms. Maize is grown in the two rainy seasons,
81 with the aim to meet household food needs (subsistence farming) (Erenstein, Kassie, & Mwangi, 2011; Erenstein,
82 Kassie, Langyintuo, et al., 2011; Speranza et al., 2008). While during the long rainy season (March-April-May)
83 multiple crops are planted, the short rainy season (October-November-December) is considered the main growing
84 season for maize in the region (Rao et al., 2011).

85 Reported smallholder maize yields often do not exceed 0.7 ton/ha. However, with optimal soil water management,
86 maize yields can easily be around 1.3 ton/ha in the semi-arid medium potential maize growing zone in south-
87 eastern Kenya (Omoyo et al., 2015). Few farmers use pesticides or improved seeds or other adaptation strategies
88 (Tongruksawattana & Wainaina, 2019) . In Kitui, Makueni and Machakos, the most preferred seed-variety is the
89 high yielding but less drought resistant Kikamba/Kinyaya variety (120 growing days) with a potential yield of
90 only 1.1 tons per hectare (Speranza, 2010; Recha et al., 2012). Trend analysis (1994-2008) shows that yields are
91 declining due to the increasing pace of recurring droughts (Nyandiko, 2014).

92 Over 97% of the smallholder farmers in this area grow maize, mainly for own consumption or local markets
93 (Brooks et al., 2009; Kariuki, 2016; Nyariki & Wiggins, 1997). It is the main staple food, providing more than a
94 third of the caloric intake, and is also the primary ingredient used in animal feeds in Kenya (Adamtey et al., 2016;
95 FAO, 2008). .. Only about 20% of the farmers are able to sell their excess crops, while 66% have to buy maize
96 to complement their own production (Muyanga, 2004).



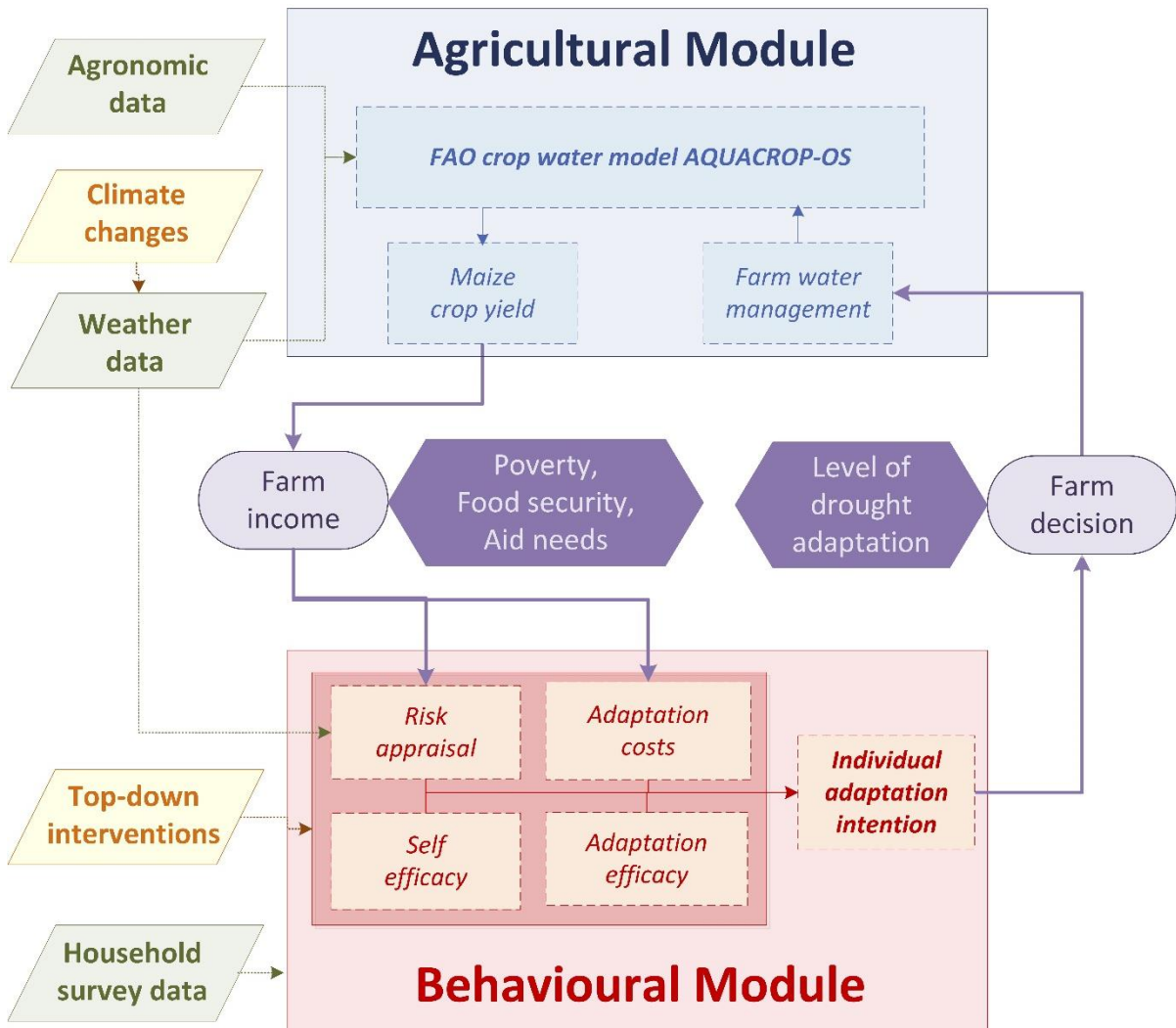
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Figure 1: Study area: dry transitional maize agro-ecological zone (right) located in South-Eastern Kenya (centre) in the Horn of Africa (left). Area where the survey data (Wens 2021) is collected is indicated with a star on the right map. Map adjusted from Barron and Okwach (Barron & Okwach, 2005)

101 **3 Model and scenario description**

102 ADOPT (fig. 2, Wens et al 2020, ODD+D (Overview, Design concept, Details + Decision) protocol in Appendix
103 A) is an agent-based model that links a crop production module to a behavioural module evaluating the two-way
104 feedback between drought impacts and drought adaptation decisions. ADOPT was parameterized with
105 information from expert interviews, a farm household survey with 260 households including a semi-structured
106 questionnaire executed in the Kitui Region, Kenya (Wens et al. 2021). Moreover, a discrete choice experiment (a
107 quantitative method to elicit preferences from participants without directly asking them to state their preferred
108 options) was executed to get information on changes in adaptation intentions under future top-down DRR
109 interventions (Wens et al. 2021). This empirical dataset feeds the decision rules in ADOPT describing farm
110 households' adaptive behaviour in the face of changing environmental conditions (drought events), social
111 networks(actions of neighbouring farmers), and top-down interventions (drought management policies). In
112 ADOPT, crop production is modelled using AquacropOS (Foster & Brozović, 2018), simulating crop growth on
113 a daily basis and producing crop yield values at harvest time twice per year. Calibrated for the Kenyan dryland
114 conditions (Ngetich et al., 2012; Wamari et al., 2007), AquacropOS considers the current water management of
115 the farm (i.e., the applied drought adaptation measures) and yields vary with weather conditions. The adaptive
116 behaviour of the farm households (agents) is modelled based on the Protection Motivation theory (PMT, Rogers
117 1975). This theory was derived as promising in an earlier study (Wens et al, 2020) and includes multiple relevant
118 factors that drive the observed behaviour of farm households (Wens et al 2021). In this application of ADOPT,
119 the model was run over 30 historical years as baseline followed by 30 years of future scenarios (combinations of
120 policy and climate changes; the start of these changes is indicated as "year 0"). Through a sensitivity analysis,
121 both the average effect of individual adaptation decisions and its endogenous model variability are analysed

122 (similar to Wens et al 2020). We used 12 different initialisations per scenario to include variations in model
 123 initialisation, the stochasticity that determines the individual adaptation decisions, and the relative weights of
 124 factors influencing behaviour (See 3.1).



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 126 **Fig. 2: ADOPT model overview, adjusted from Wens et al., 2020. Description of the model (Overview, , Design concepts**
 127 **& Details) in Appendix A.**

128 3.1 Individual adaptive behaviour in ADOPT

129 Various soil water management practices, further called drought adaptation measures, can be adopted by
 130 smallholder farmers in ADOPT. There are shallow wells to provide irrigation water, the option to connect these
 131 to drip irrigation infrastructure, and Fanya Juu terraces as on-farm water harvesting techniques. Moreover, a soil
 132 protection measure reducing the evaporative stress, mulching, is included. These measures are beneficial in most
 133 – if not all – of the years and have a particularly good effect on maize yields in drought years. Nonetheless, current
 134 adoption rates of these measures are quite varied and often remain rather low (Gicheru, 1990; Kiboi et al., 2017;
 135 Kulecho & Weatherhead, 2006; Mo et al., 2016; S. Nngigi, 2019; S. N. Nngigi et al., 2000; Rutten, 2004; Zone,
 136 2016).

137 ADOPT applies the Protection Motivation Theory, a psychological theory often used to model farmer's bounded
138 rational adaptation behaviour (Schrieks et al 2021). It describes how individuals adapt to shocks such as droughts
139 and are motivated to react in a self-protective way towards a perceived threat (Grothmann & Patt, 2005; Maddux
140 & Rogers, 1983). Four main factors determining farmers' adaptation intention under risk are modelled: (1) risk
141 perception is modelled through the number of experienced droughts and number of adopted measures, household
142 vulnerability, and experienced impact severity. Moreover, trust in early warnings is added, which can influence
143 the risk appraisal if a warning is sent out. Coping appraisal is modelled through a (2) farmers' self-efficacy
144 (household size / labour power, belief in God, vulnerability), (3) adaptation efficacy (perceived efficiency, cost
145 and benefits, seasons in water scarcity, choices of neighbours, number of measures), and (4) adaptation costs
146 (farm income, off-farm income, adaptation spending, access to credit). These four PMT factors receive a value
147 between 0 and 1 and define a farmer's intention to adopt. Which smallholder farmers adopt which measures in
148 which years is then stochastically determined based on this adaptation intention. More information regarding the
149 decision making can be found in Appendix A.

150 **3.2 Drought risk indicators in ADOPT**

151 In ADOPT, annual maize yield influences the income and thus assets of the (largely) subsistence farm households.
152 This influence is indirect, because the farm households are assumed to be both producers and consumers, securing
153 their own food needs. The influence is also a direct one, because these farm households sell their excess maize
154 on the market at a price sensitive to demand and availability. Farm households who cannot satisfy their food needs
155 by their own production, turn to this same market. They buy the needed maize – if they can afford it and if there
156 is still maize available on the market. If they do not have the financial capacity or if there is a market shortage,
157 they are deemed to be food insecure. Their food shortage (the kilogram maize short to meet household food
158 demand) is multiplied by the market price to estimate their food aid needs. Adding the farm income of the
159 household with their income from potential other sources of income, it is estimated whether they fall below the
160 poverty line of 1.9 USD per day. As climate and weather variability causes maize yields to fluctuate over time,
161 so do the prevalence of poverty, the share of households in food insecurity and the total food aid needs. These
162 factors can be seen as proxies for drought risk and were evaluated over time.

163 **3.3 Climate change scenarios**

164 Multiple climate change scenarios – all accounting for increased atmospheric carbon dioxide levels - were tested:
165 a rising temperature of 10%, a drying trend of 15%, a wetting trend of 15%, and various combinations of these.
166 The warming and drying trends were based on a continuation of the trends observed in the last 30 years of daily
167 NCEP temperature (Kalnay et al., 1996) and CHIRPS precipitation (Funk et al., 2015) data (authors' calculations;
168 similar trends found in (Gebrechorkos et al., 2020)). The wetting trend was inspired by the projections from most
169 climate change models which predict an increase in precipitation in the long rain season – a phenomenon known
170 as the 'East African Climate Paradox'(Gebrechorkos et al., 2019; Lyon & Vigaud, 2017; Niang et al., 2015). The
171 no change scenario was a repetition of the baseline period, without changing precipitation or temperature hence

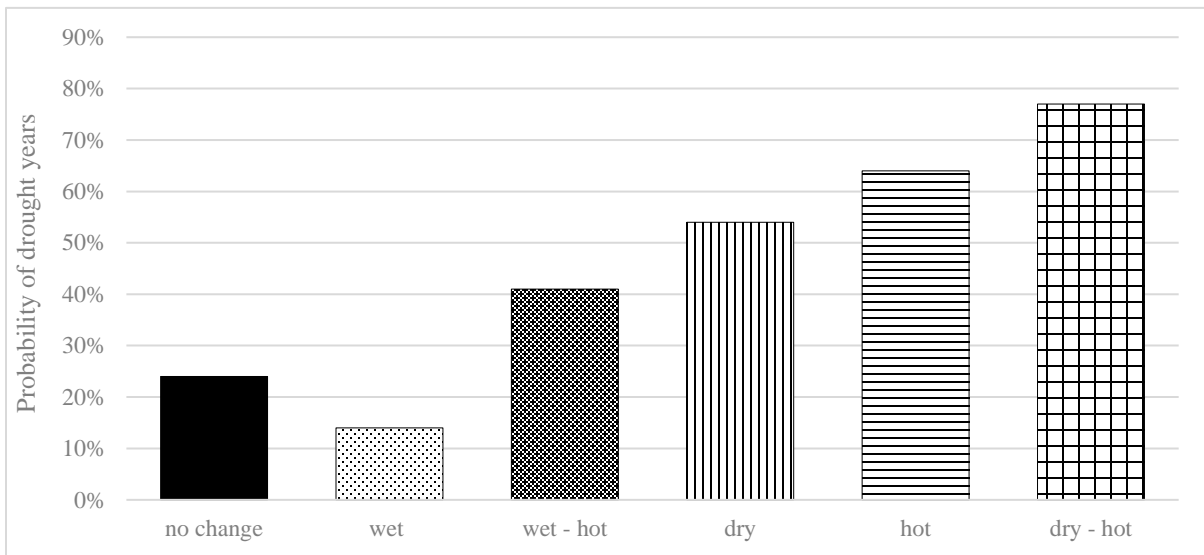
172 only elevated carbon dioxide levels. Reference evaporation was calculated for each scenario using the Penman-
 173 Monteith model and thus influenced by temperature changes (Allen, 2005; Droogers & Allen, 2002).

174 **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

175 These trends were added to time series of 30 years of observed data. While such approach does not account for
 176 an increased variability, it allows to account for the temporal coherence in the data and the interrelationships
 177 among different weather variables (weather generators – another option to downscale projected climate - have
 178 still some progress to make in order to accurately account for extreme events (Ailliot et al., 2015; Mehan et al.,
 179 2017)). This resulted of 30 years of synthetic ‘future’ data, for each of the six - wet, hot-wet, hot, dry, hot-dry and
 180 no change - scenarios . While they not have a known probability of occurring, they enable **testing the robustness**
 181 of the on-farm adaptations and top-down drought disaster risk reduction strategies under changing average hydro-
 182 meteorological conditions.

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

187 Droughts, here defined as at least three months with standardized precipitation index (SPEI) values below - 1 ,
 188 have a different rate of occurrence under these different future climate scenarios (Fig. 3). SPEI is calculated
 189 through standardizing a fitted **GEV** distribution over the historical monthly time series and superimposing this
 190 onto the climate scenario time series. Under the no change scenario, 25% of the thirty simulated years fall below
 191 this threshold. Under the wet scenario, fewer droughts occur (15% of the years), but under the dry scenario, the
 192 number of droughts years more than doubles (54% of the years). Temperature is dominant over precipitation is
 193 determining drought conditions, as under the hot-wet scenario, 41% drought years are recorded, and under hot-
 194 dry conditions, 78% of the years can be considered drought years.

195 3.4 Drought risk reduction intervention scenarios

196 Kenya Vision 2030 for the ASAL promotes drought management through extension services and aims to increase
197 access to financial services such as affordable credit schemes (Government of Kenya, 2012; Kenya, 2016).
198 Besides, building on the Ending Drought Emergencies plan, the National Drought Management Authority
199 prioritizes the customization, improvement and dissemination of drought early warning systems. It aims to
200 establish trigger levels for ex-ante cash transfer so as to upscale drought risk financing (Government of the
201 Republic of Kenya, 2013; National Drought Management Authority, 2015; Republic of Kenya, 2017). Improved
202 extension services tailored to the changing needs of farm households (Muyanga & Jayne, 2006), a better early
203 warning system with longer lead times (Deltares, 2012; van Eeuwijk, n.d.), ex-ante cash transfers to the most
204 vulnerable when a drought is expected (Guimarães Nobre et al., 2019) and access to credit-markets (Berger et al.,
205 2017; Fan et al., 2013) are all assumed to increase farmers' intention to adopt new measures.

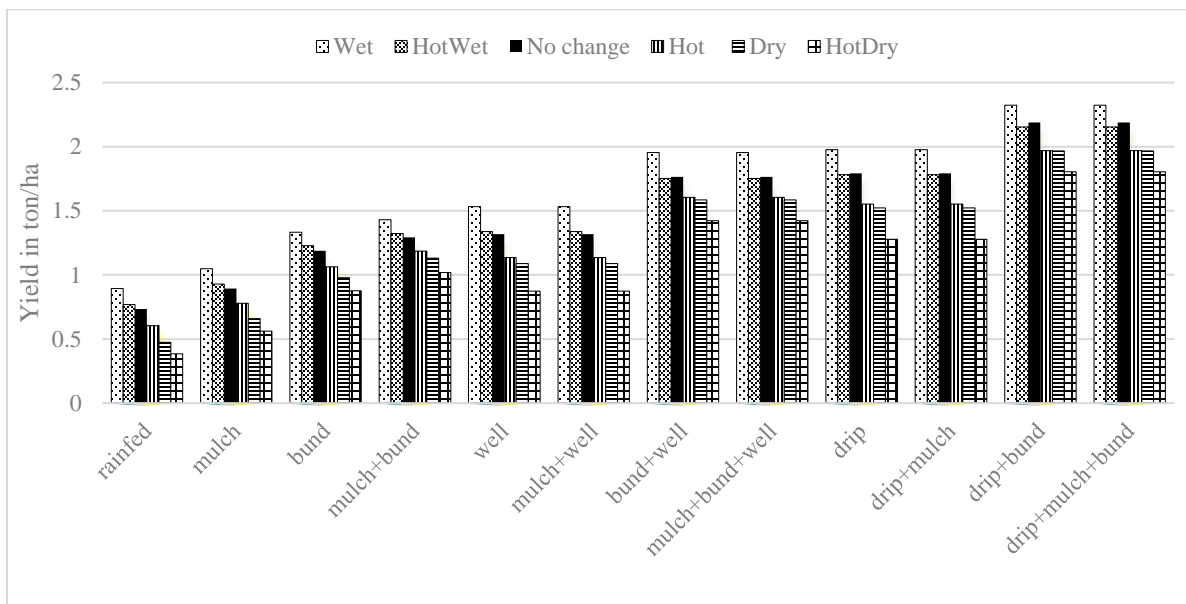
206 As shown in Wens et al (2021), extension services are best offered to younger, less rich and less educated people,
207 or to those who already adopted the most common measures. Similarly, early warning systems are appreciated
208 more by less educated, less rich farmers, or those not part of farmer knowledge exchange groups. The ex-ante
209 cash transfer instigates those who spend already a lot of money on adaptation, to adopt more expensive measures
210 the most. Access to credit is preferred by less rich farmers, who have a larger land size, are members of a farm
211 group, went to extension trainings, have easy access to information and/or are highly educated (Wens et al. 2021).
212 In this application of ADOPT, the effect of these four interventions - extension services, early warning systems,
213 ex-ante cash transfer and credit schemes - were tested individually. Additionally, three scenarios, combining
214 different types of interventions, were evaluated, all initiated in year "0" in the model run.

- 215 1. Reactive policy intervention "supporting drought recovery": Emergency aid is given to farmers who lost their
216 livelihoods after drought disasters; this food aid is distributed to farmers who are on the verge of poverty to
217 avoid famine.
- 218 2. Pro-active policy intervention plan "preparing for drought disasters": Early warnings are sent out each season
219 if a drought is expected. This is assumed to raise all farmers' risk appraisal with 20%. Ex-ante cash transfers
220 are given to all smallholder farmers (those without income off-farm and without commercialisation) to
221 strengthen resilience in the face of a drought. This is done when severe and extreme droughts (SPEI <-1, and
222 <-1.5) are expected that could lead to crop yield lower than respectively 500kg/ha and 300kg/ha. Money
223 equivalent to the food insecurity following these yields is paid out to farmers with low external income
224 sources. Moreover, like in the reactive government scenario, emergency aid is given to farmers who need it.
- 225 3. Prospective policy intervention plan (UNDRR 2021) "mitigating (future) drought disasters": Credit rates are
226 lowered so that it is affordable to people to take a loan for adaptation measures, at an interest rate of 2% and
227 a pay-back period of five years. Besides, frequent trainings are given in communities with poor practices to
228 improve their capacity related to drought adaptation practices for agriculture. Moreover, like in the proactive
229 government scenario, an improved early warnings system is set up and ex-ante cash transfer is given. Lastly,
230 emergency aid is given to farmers who need it.

231 **4. Results**

232 **4.1 Maize yield under different adaptation measures and future climate scenarios**

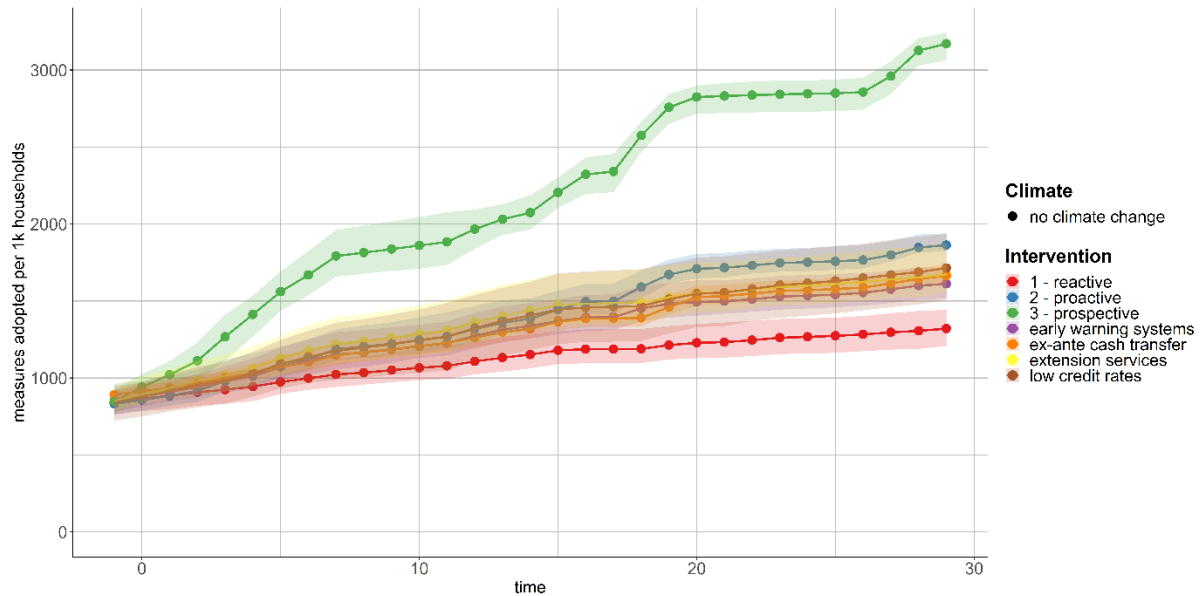
233 The annual average maize yields under the different climate scenarios, for the four on-farm drought adaptation
234 measures implemented in ADOPT - mulch, Fanya Juu bunds, shallow well and drip irrigation -, were calculated
235 using AquacropOS (Fig. 4). Under wetter future climate conditions, maize yields are expected to increase under
236 all management scenarios, with mulch having a particular positive effect on the soil moisture conditions
237 throughout the full growing season. Hotter climate conditions reduce yields slightly: the assumptions in this
238 model on the frequency and amount of manual irrigation or drip irrigation water are not sufficient to diminish this
239 effect, even under wetter conditions. Paired with drier conditions, this hotter future has dramatically negative
240 effects on yields, showing on average 28% lower yields compared to the no climate change scenario over all
241 management scenarios.



242
243 **Fig. 4: Average maize yield under different drought adaptation measures and different future climate scenarios.**

244 **4.2 The adoption of adaptation measures over time**

245 In ADOPT, all evaluated top-down interventions increased the adoption rate of the evaluated adaptation measures
246 compared to the reactive “no intervention” scenario (Fig.5): reduced credit rates, improved early warning systems,
247 tailored extension services, and ex-ante cash transfers, as well as the proactive and prospective scenarios lead to
248 increases in adoption as compared to the reactive scenario (colours in Fig. 5).



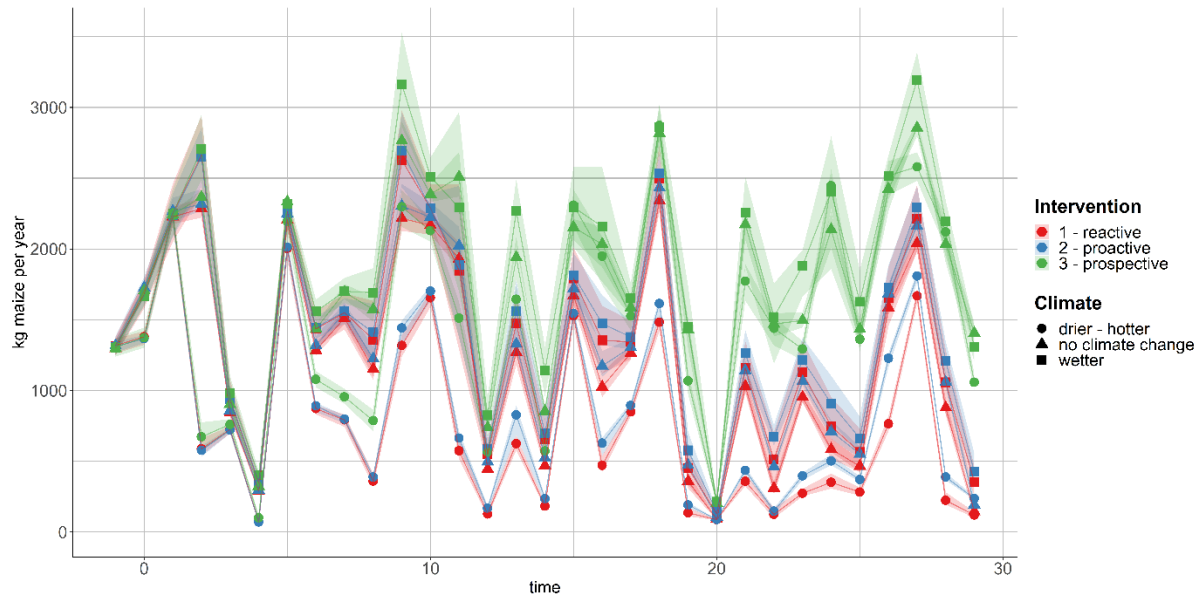
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250 **Fig. 5: Total amount of measures adopted per 1000 initialized households under no climate change, averaged over all**
 251 **runs. The shaded area indicates the variation - uncertainty introduced by different model initialisations and by**
 252 **different relative importance of the PMT factors on the decisions of households (sensitivity analysis). Year 0 initiates**
 253 **policy drought risk reduction interventions (indicated with different line colours).**

254 Looking into detail to the effect of possible policy interventions (Fig. 5, table B2 in Appendix B), affordable
 255 credit schemes had the highest effect on the adoption rate of drought adaptation measures. Furthermore, ex-ante
 256 cash transfers (which cannot be seen as large sums of investment money but as a mere means to keep families
 257 food secure) were more effective to increase adoption of the more affordable measures. Indeed, richer families
 258 mostly had already adopted these measures before policy interventions were in place. Extended extension service
 259 training increased the adoption of less popular measures and decreased the adoption of the popular but not as
 260 cost-effective Fanya Juu terraces. Early Warning Systems had more effect in the wetter climate conditions. The
 261 dry-hot scenario has so many drought episodes that risk perception is automatically high while the alert lowers
 262 when droughts become scarcer in the less dry scenarios.

263 Overall, although the processes through which the interventions support households to adapt differ significantly,
 264 the differences in eventual adoption rate under the different interventions were small (they overlap in uncertainty
 265 interval). Also, the effect of climate change on the adoption rate (Figure B1, Table B2 in Appendix B) was rather
 266 small when evaluating the **reactive (no intervention)** scenario. However, with interventions, the climate change
 267 scenarios differed more.

268 When examining the effect of the three intervention scenarios (Figure B2 in Appendix B; table B2 in Appendix
 269 B), it is clear that implementing multiple policies at once resulted in a stronger increase in adoption: a proactive
 270 and prospective intervention plan increased the adoption of different adaptation measures with respectively 40%
 271 and 140% more than under the “reactive, no climate change” scenario where no intervention takes place. Both a
 272 proactive and prospective approach increased the adoption of cheaper adaptation measures to close to 100% of
 273 the farm households. For the more expensive measures, the proactive scenario showed to be less effective while
 274 the prospective scenario reached quite high adoption rates in the more extreme climate 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 policy intervention scenarios. The shaded area indicates the variation - uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households (sensitivity analysis)

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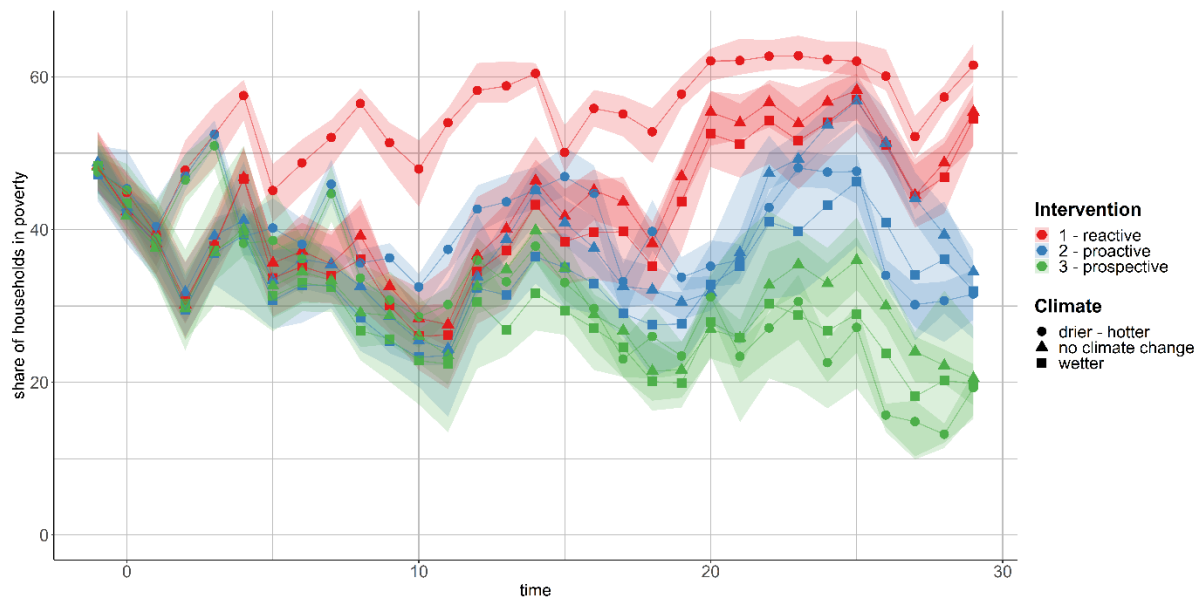
The adoption of adaptation measures by households influenced their maize yield and thus affected the average and median maize harvest under the different future climates and drought risk reduction interventions (Fig. 6). This becomes clear comparing the first thirty baseline years with the following thirty scenario years: When no policy 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 prospective 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 under this intervention scenario did offset a potentially harmful drying climate trend.

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4.3 Drought risk dynamics under policy and climate change

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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 or by the adoption of new adaptation measures, could drive farm household in or out of poverty. Running ADOPT with a reactive and no climate change scenario, a slight increase of 5 percentage points (pp) in poverty levels was visible. Poverty levels increased up to 15pp compared to the baseline situation, when a dryer and/or hotter climate scenario was run. A proactive intervention plan reduced poverty by 11pp under no climate change. In the dry-hot climate scenario this combination of improved early warning systems and ex-ante cash transfers lead to reductions of 20-30pp compared to the baseline years. However, the prospective government scenario showed the most prominent results, projecting reductions of 45pp under no climate change and around 60pp under dryer and hotter climate conditions.

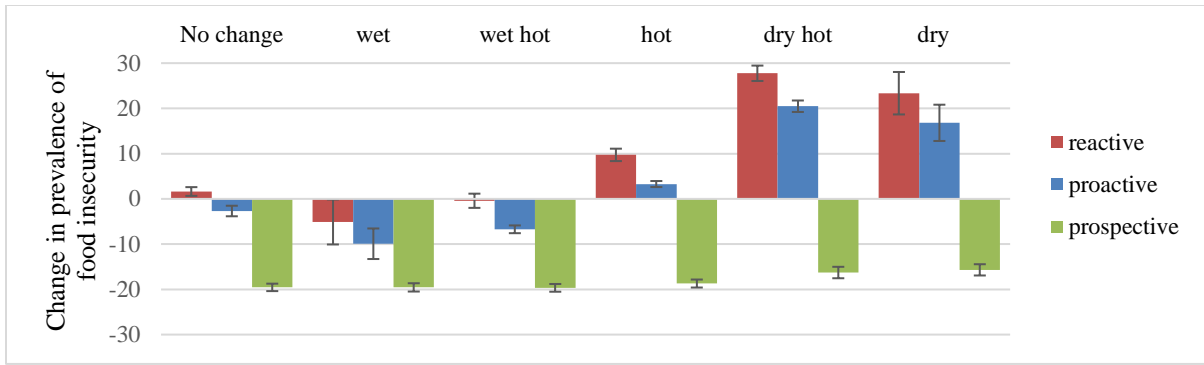


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300 **Fig. 7: Share of households in poverty (earning under the 2USD/day income line, under different climate and policy**
 301 **intervention scenarios). The shaded area indicates the variation - uncertainty introduced by different model**
 302 **initialisations and by different relative importance of the PMT factors on the decisions of households (sensitivity**
 303 **analysis).**

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

311 Improving extension services or providing ex-ante cash transfers individually showed on average 7.5% more
 312 reduction in food insecurity than the reactive government scenario. Improved early warning systems showed on
 313 average - over all climate scenarios- an increased reduction of 4.5%. It should be kept in mind that ADOPT does
 314 not consider (illicit) coping activities in the face of droughts such as food stocking **or charcoal burning**. However,
 315 both of them might reduce the food security threat. Credit schemes at 2%, individually, lead to more than 8%
 316 reduction in food insecurity levels as compared to the reactive scenario; but even then, on average net food
 317 insecurity rates increase due to climate change. A proactive intervention resulted in a food insecurity rate which
 318 is 6 percent points lower than under the reactive scenario; but still showed increases in the prevalence of food
 319 insecurity under hotter and drier conditions. A prospective intervention, combining all four interventions, was
 320 able to consistently reduce the food insecurity levels over time, even under the dry-hot climate scenario. This
 321 scenario was able to counteract the increase in food insecurity, achieving a reduction of households in food
 322 shortage over time with on average 28% compared to the reactive scenario, all climate scenarios considered.



323

324 **Fig. 8: Absolute change (average and standard deviation introduced by sensitivity analysis - variation caused by**
 325 **different model initialisations and by different relative importance of the PMT factors on the decisions of households)**
 326 **in average share of households in food shortage of the 20 last years of scenario run, compared to the first 20 years of**
 327 **baseline run before “year 0“, under different climate and policy intervention scenarios. ADOPT model output.**

328 Expressing drought impacts in average annual food aid required (in USD) can help to evaluate the effect of
 329 different climate change scenarios or different policy intervention scenarios on the drought risk of the community.
 330 These estimations are translated to USD, assuming a maize price for shortage markets, as price volatility is
 331 considered. Table 2 shows the change in aid needs compared to the no-climate change, no-top-down intervention
 332 baseline period (based on the 1980-2000 situation). When assuming no climate change, it seemed that the
 333 community is stable, only slightly increasing the share in vulnerable households. More measures were adopted as
 334 information is disseminated through the farmer networks, but those who stay behind will face lower sell prices as
 335 markets get more stable and have a harder time accumulating assets. Under wetter conditions, reductions in
 336 drought emergency aid did reduce. However, drier, hotter climates had a detrimental effect on the food needs,
 337 with more vulnerable people crossing the food shortage threshold.

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

344 **Table 2: Change in aid needs (%) in 2030-2050 compared to 1980-2000 (average and standard deviation introduced by**
 345 **sensitivity analysis - variation caused by different model initialisations and by different relative importance of the PMT**
 346 **factors on the decisions of households) under different climate and policy intervention scenarios. ADOPT model**
 347 **output.**

	No change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive scenario</i>	4 (+-4)%	-29(+20)%	-11(+6)%	37(+6)%	117(+6)%	94(+24)%
<i>Ex ante cash transfer</i>	-2(+4)%	-31(+15)%	-20(+5)%	24(+5)%	92(+3)%	76(+17)%
<i>Early warning system</i>	-6(+6)%	-42(+18)%	-24(+6)%	25(+5)%	109(+8)%	86(+25)%
<i>Extension services</i>	-20(+7)%	-49(+17)%	-33(+6)%	15(+4)%	96(+9)%	71(+15)%
<i>Credit at 2% rate</i>	-24(+10)%	-50(+18)%	-33(+8)%	10(+12)%	86(+12)%	62(+28)%
<i>Proactive scenario</i>	-15(+6)%	-48(+12)%	-37(+3)%	13(+5)%	73(+6)%	58(+17)%
<i>Prospective scenario</i>	-80(+1)%	-81(+1)%	-82(+1)	-78(+2)%	-68(+3)%	-66(+4)%

348 5. Discussion

349 5.1 The effect of early warning, extension services, ex-ante transfers and low interest rates

350 Under a reactive strategy (“no intervention”) and assuming no climate change, a slow but steady adoption of
351 mulch, Fanya Juu, shallow well and irrigation practices is estimated. This is a result of an ever increasing
352 information diffusion through the farmer networks and existing extension services, as also found in Hartwich et
353 al., 2008a; van Duinen et al., 2016a; Villanueva et al., 2016; Wossen et al., 2013. Yet, multiple smallholder
354 households still suffer from the effects of droughts, indicated by the elevated food insecurity rates and poverty
355 rates. While some can break the cycle of drought and subsequent income losses, others are trapped by financial
356 or other barriers and end up in poverty and recurring food insecurity. This is also found by e.g., Enfors & Gordon,
357 (2008); Mango et al., (2009); Mosberg & Eriksen, (2015); Sherwood, (2013). In the reactive scenario, it is clear
358 that adaptation intention is limited by factors such as a low risk perception, high (initial) adaptation costs, a limited
359 knowledge of the adaptation efficacy or a low self-efficacy. Some of these barriers are alleviated through the
360 different government interventions.

361 As compared to this reactive scenario an increased rate of adoption is observed for all policy interventions. This
362 translates into a comparatively lower drought risk (expressed by the indicators: community poverty rate, food
363 security and aid needs). While initially extension services have the largest effect on the adoption of on-farm
364 drought adaptation measures, over time access to credit results in the highest adoption rates and is also estimated
365 to decrease emergency aid the most. The former, alleviating the knowledge (self-efficacy) barrier, increases
366 adoption under no climate change with 27% as compared to no intervention. It is indeed widely recognized as an
367 innovation diffusion tool in different contexts (e.g., Aker, 2011; Hartwich et al., 2008b; Wossen et al., 2013). The
368 latter, alleviation the financial (adaptation costs) barrier, increases adoption under no climate change with 30%
369 as compared to no intervention. It is also found to be an effective policy to reduce poverty in Ghana by Wossen
370 and Berger (Wossen & Berger, 2015). Ex-ante cash transfers also tackle the financial barrier but less effectively
371 (the cash sum is small and fixed – only significant for less wealthy households), increasing adoption under no
372 climate change with 25% as compared to no intervention. This matches empirical evidence on the positive effects
373 of ex-ante cash transfers (Asfaw et al., 2017; Davis et al., 2016; Pople et al., 2021). However, ADOPT model
374 estimations might be an underestimation as the model does not account for many preparedness strategies of
375 households such as stocking up food while the price is still low, fallowing land to reduce farm expenses, or
376 searching for other sources of income (Khisa & Oteng, 2014). Seasonal early warning systems, which raise
377 awareness of upcoming droughts, increase the adoption of measures with 22% as compared to no intervention.
378 Early warnings have a stronger effect on the adoption of mulching or Fanya Juu (cheaper measures, lower
379 financial barrier) than on drip irrigation. Clearly, the positive effect of the interventions on household resilience
380 varies, which is confirmed by the empirical findings of Wens et al. 2021.

381 The proactive government scenario, “preparing for drought disasters” by improving early warning systems and
382 supporting ex-ante cash transfers, has a larger effect on drought risk. However, this effect is not as much as the
383 sum of the effect of the two interventions. In contrast, the prospective government scenario “mitigating drought
384 disasters” by combining all four interventions, alleviates multiple barriers to adoption at once. This creates a

385 significant, non-linear increase in adoption, matching the significant positive correlation between the preferences
386 for extension, credit, early warning in Wens et al. 2021. Consequently, this scenario results in a clear growth in
387 resilience of the farm households, shown in more stable income, lower poverty rates and less food insecurity.

388 **5.2 The robustness of drought risk reduction interventions under climate change**

389 Climate change influences the effectivity of the measures as well as farm households' experience with droughts.
390 Under all climate change scenarios, a lower adoption of adaptation measures compared to the "no climate change"
391 assumption is observed. This could be explained by the fact that the perceived need to adapt is lower under wet
392 conditions and the financial strength to adapt is lower under dry or hot conditions. This highlights two different
393 barriers to adoption: risk appraisal lowers when the occurrence of drought impacts is less frequent, while coping
394 appraisal lowers due to experiencing more drought impacts. This link between drought experiences, poverty and
395 adaptation was also found in other studies (e.g., Gebrehiwot & van der Veen, 2015; Holden, 2015; Makoti &
396 Waswa, 2015; Mude et al., 2007; Oluoko-Odingo, 2011; Winsen et al., 2016)

397 While their effect on the adoption rates seems rather small, the diverse climate change scenarios have a distinctly
398 different effect on the evolution of drought risk in the rural communities. Due to the adaptation choices of the
399 farm households, average maize harvests are estimated to slightly increase under the "no climate change"
400 scenario. A major increase is estimated under wet and wet-hot conditions where both increased adoption and
401 better maize producing weather conditions play a role. Under hot, dry and dry hot conditions, the average
402 household harvests are estimated to decrease (also found in Wamari et al., 2007). Increases in median and mean
403 assets (household wealth) are estimated slightly increase under the no climate change scenario. In this case,
404 adaptation efforts are able to reducing the drought disaster risk. Drier climates might lead to decreases in median
405 and mean assets, if farm households are not supported through top-down interventions, Hotter climates are
406 estimated to result decreased median but increased average assets of the households. In this case, adaptation rates
407 are not high enough to avoid increasing drought risk for the median households.

408 The proactive government scenario is estimated to level poverty and food security under hotter or drier climate
409 change scenarios. The prospective government scenario is the only scenario estimated to reduce emergency aid
410 under all possible future climates. However, it should be noted that it takes one to two decades to make a
411 significant difference between the reactive stance and prospective intervention plan. In other words: with climate
412 change effects already visible through an increased frequency of drought disasters, and more to be expected within
413 the following 10-20 years, prospective intervention should be started now in order to be benefit from the increased
414 resilience in time under any of the evaluated futures.

415 **5.3 ADOPT as a dynamic drought risk adaptation model**

416 In the past decade, the use of **ABMs** in *ex-post* and *ex-ante* evaluations of agricultural policies and agricultural
417 climate mitigation has been progressively increasing (Huber et al., 2018; Kremmydas et al., 2018). A pioneer in
418 agricultural ABM is Berger (2001) who couples economic and hydrologic components into a spatial multi-agent
419 system. This is followed more recently by for example Berger and Troost (2011), Van Oel and Van Der Veen

420 (2011), Mehryar et al. (2019) and Zagaria et al. (2021). The socio-hydrological, agent-based ADOPT model
421 follows this trend in that it fully couples a biophysical model—AquacropOS—and a social decision model—
422 simulating adaptation decisions using behavioural theories—through both impact and adaptation interactions.
423 The initial ADOPT model setup was created through interviews with stakeholders (Wens et al. 2020), and the
424 adaptive behaviour is based on both existing economic – psychological theory and on empirical household data
425 (Wens et al. 2021). The assumption of heterogeneous, bounded rational behaviour is addressed yet only by a few
426 risk studies (e.g. Van Duinen et al. 2015, 2016; Hailegiorgis et al. 2018, Keshavarz and Karami 2016, and Pouladi
427 et al. 2019). These studies have implemented empirically supported and complex behavioural theories in ABMs
428 similarly to ADOPT (Schrieks et al. 2021; Jager, 2021; Taberna et al., 2020; Waldman et al., 2020).
429 ADOPT differs from these models, however, through its specific aim to evaluate households and community
430 drought disaster risk beyond the number of measures adopted, crop yield, or water use. Rarely (except e.g., Dobbie
431 et al 2018) do innovation diffusion ABM use socio-economic metrics to evaluate drought impacts over time –
432 while such risk proxies are of great social relevance. As such, ADOPT evaluates the heterogeneous changes in
433 drought risk for farm households, influenced by potential top-down drought disaster risk reduction (DRR)
434 interventions. It does so through simulating their influence on individual bottom-up drought adaptation decisions
435 by these farm households and their effect on socio-economic proxies for drought risk (poverty rate, food security
436 and aid needs). To our knowledge, this is rather novel in the field of DRR and drought risk assessments.

437 **5.4 Uncertainties in ADOPT and limitations in investigated measures and interventions**

438 While yield data has been validated over the historical period (Wens et al. 2020), the model output cannot be
439 used as a predicting tool. This would require more extensive validations for which, currently, data is not available.
440 Such data would include longitudinal information on household vulnerability and adaptation choices from areas
441 where certain policies are being implemented, or detailed data on aid needs for the case study area. The past
442 average poverty and food insecurity rates matched observations (Wens et al. 2020). However, absolute amounts
443 of emergency aid needs are sensitive to the averages and fluctuations of household assets which proved harder to
444 verify. Besides, poverty and food insecurity depend also on external, food or labour market and other influences
445 which might change towards the future. Moreover, the simulated climate scenarios are not entirely realistic
446 (because variability changes are ignored and because the synthetic future data is created based on statistics rather
447 than physical climate and weather system changes). Moreover, the East African Climate Paradox (Funk et al.,
448 2021) creates its own set of challenges predicting future weather conditions in the study area.
449 Unavoidably, multiple possible smallholder adaptation measures are omitted in this study: many more agricultural
450 water management measures, agronomic actions, and other options under the umbrella of climate-smart
451 agriculture, exist. Besides, only four different policy interventions are evaluated while various other exists. Costs
452 of these top-down interventions are unknown, making cost-benefit estimates regarding drought risk reduction
453 strategies not possible for this study. Studying additional measures or interventions is be possible using the
454 ADOPT model, but requires (the collection of) more data for parametrization and calibration.

455 Another future improvement to the model could be to directly sample the empirical household survey data (Wens
456 et al 2020) to create a synthetic agent set. Now, the creation of agents (households) with different characteristics
457 is drawn from distribution functions based on frequencies in the empirical data. Such one-to-one data-driven
458 approach is similar to microsimulation and gaining popularity among ABMs (Hassan et al 2010). Lastly, the
459 model application does assume no shifts in the processes underlying weather and human decision making: both
460 the synthetic future weather situation and the decision making processes are based on past observations. To avoid
461 the effect of systemic changes and black swan effect, only 30 “future” years are modelled.
462 Because the model setup could not be fully validated, and scenarios do not provide a complete overview of all
463 possibilities, this study does not claim to provide a prediction of the future for south-eastern Kenya. However,
464 ADOPT is meant to – rather than forecast drought impact - increase understanding of the differentiated effect of
465 adaptation policies: the relative differences in the risk indicators are informative for the comparison of these top-
466 down interventions under different changes in temperature and precipitation. This study showcases the application
467 of ADOPT as a decision support tool. It evaluates the robustness of a few, dedicatedly chosen policy interventions
468 on farm household drought risk under climate scenarios that are deemed to be relevant for the specific area. Future
469 research can use ADOPT to study the differentiated effect of these interventions on different types of households,
470 in order to tailor strategies and target the right beneficiaries of government interventions. .

471 **6. Conclusion**

472 Top-down interventions, providing drought and adaptation information as well as supporting the capacity to act
473 on the basis of this information, are needed to increase the resilience of smallholder farmers to current and future
474 drought risk. However, to which extent these interventions will steer farmers’ intention to adopt drought
475 adaptation measures, hence how effective they are in reducing the farm household drought risk, often remains
476 unknown. In this study, the agent-based drought risk adaptation model ADOPT is applied to evaluate the effect
477 of potential future scenarios regarding climate change and policy interventions on agricultural drought risk in
478 south-eastern Kenya. The smallholder farmers in this region face barriers to adopt drought adaptation measures
479 such as mulching, Fanya Juu terraces, shallow wells, and drip irrigation, to stabilize production and income.
480 ADOPT simulates their adaptive behaviour, influenced by drought occurrences under changing climate
481 conditions. Adaptive behaviour is also influenced by top-down (non-)government drought risk reduction
482 interventions such as the introduction of ex-ante cash transfers, affordable credit schemes, improved early warning
483 systems and tailored extension services. We demonstrate that the investigated interventions all increase the
484 uptake of adaptation measures as compared to the reactive scenario under no climate change (business-as-usual).
485 Extension services (+27% uptake) multiply adaptation knowledge and thus increase self-efficacy among the
486 smallholders, which raises the adoption of less popular drought adaptation measures. Accessible credit schemes
487 (+30% uptake), alleviating a financial barrier, are effective especially for more expensive drought adaptation
488 measures. Early warning systems (+22% uptake), creating risk awareness, are more effective in climate scenarios
489 with less frequent drought. Ex-ante cash transfers (+25% uptake) allow the least endowed households to climb

490 out of the poverty trap by adopting low-cost drought adaptation measures and thus reducing future shocks. The
491 effect of climate change on the adoption of adaptation measures is limited.

492 Moreover, this study proves that alleviating only one barrier to adoption has a limited result on the drought risk
493 of the farm households. Under the pro-active scenario (+40% uptake), combining early warning with ex-ante cash
494 transfers, smallholder farmers are better supported to adopt drought adaptation measures and to create, on average,
495 more wealth. However the effect of climate change on farm households risk differs significant under this proactive
496 scenario. While for wetter conditions, this scenario is able to increase food security and reduce poverty, this is
497 not sufficient to diminish the need for external food aid under every evaluated climate scenario. Only by
498 combining all four interventions (+139% uptake), a strong increase in the adoption of measures is estimated.
499 Simultaneously increasing risk perception, reducing investment costs, and elevating self-efficacy, creates
500 nonlinear synergies. Under such prospective government approach, ADOPT implies significantly reduced food
501 insecurity, decreased poverty levels, and drastically lower drought emergency aid needs after 10 to 20 years,
502 under all investigated climate change scenarios.

503 This study suggests that, in order to reach the current targets of the Sendai Framework for Disaster Risk, which
504 aims at building a culture of resilience, and to achieve Sustainable Development Goals “zero hunger”,
505 “sustainable water management” and “climate resilience”, a holistic approach is needed. While we present a
506 proof-of-concept rather than predictive model, the results improve the understanding of future agricultural
507 drought disaster risk under socio-economic, policy and climate trends. We provide evidence that agent-based
508 models such as ADOPT can serve as decision support tools to tailor drought risk reduction interventions under
509 uncertain future climate conditions: More research into the heterogeneous effect of the investigated top-down
510 interventions on households’ adaptation decisions and drought risk can provide information for the effective and
511 efficient tailoring of the policy interventions. However, from this study, it is clear that multiple interventions -
512 both (risk and adaptation) information provision and the creation of action perspective - should be combined to
513 build a sustainable future for smallholder farmers in Kenya’s drylands.

514 **Appendices**

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

516 **I. Overview**

517 **I.i Purpose**

518 **What is the purpose of the model?**

519 The purpose of ADOPT is to improve agricultural drought disaster risk assessments by including the complex
520 adaptive behaviour of smallholder farmers. The ADOPT model simulates the welfare (poverty level, food security
521 & aid needs) of smallholder farm households over time as a function of climate effects on agricultural production,
522 mitigated by implemented adaptation measures, and simulates the adoption of such measures as a function of
523 economic, social and psychological household characteristics. Understanding the two-way feedback between
524 households' adaptation decisions and maize yield losses over time can help optimize drought impact estimations
525 under climate and policy changes. ADOPT can be used to evaluate the adoption rate of adaptation measures under
526 different climate and policy scenarios hence contrast their effect on the drought disaster risk – approximated by
527 food security and welfare - of smallholder farmers.

528 **For whom is the model designed?**

529 The ADOPT model can allow scientists to increase their understanding of the socio-hydrological reality of
530 drought disaster risk and drought adaptation in a smallholder farming context. It can also help decision makers to
531 design drought policies that target specific farm household and evaluate the effect of these policies on their
532 drought vulnerability.

533 **I.ii Entities, state variables, and scales**

534 **What kinds of entities are in the model?**

535 The agents in ADOPT are individual farm households that have a farm of varying size and potentially an off-farm
536 income source. Two other entities exist: the crop land (multiple fields) that yields maize production and is owned
537 by the farm households, and the market (one) where maize is sold and bought.

538 **By what attributes are these entities characterized?**

539 Farm households (see UML, figure A.1) have a farm – characterised by its farm size and the adaptation measures
540 implemented on it-. They also have a family size, a household head (male/female) with a certain age and education
541 level, financial assets (wealth, expressed in USD), off-farm employment, and farm, food and other expenses.
542 Household heads have a memory regarding past drought impacts, have a perception about their own capacity,
543 and, in varying degrees, have information about potential adaptation measures.

544 Crop land (farms) (see UML, figure A.1), belonging to households, produce maize under changing weather
 545 conditions, influenced by potential adaptation measures affecting water management conditions. The market (see
 546 UML, figure A.1) is influenced by local production and consumption, which results in a variable maize price
 547 depending on the balance between supply and demand. In the presented case study, we consider relatively isolated
 548 areas, less subjected to globalized market systems: maize price is variable following the total amount of locally
 549 produced maize to replicate the observed price volatility (with minimum and maximum prices derived from
 550 FEWSnet) during years of reduced production.



551
 552 **Figure A1. UML diagram**

553 **What are the exogenous factors / drivers of the model?**

554 Two exogenous factors influence the farm household systems: daily weather (influenced by gradual climate
555 change) and drought disaster risk reduction policies (top-down policy interventions supporting smallholder
556 farmers). The first factor might alter the frequency and severity of droughts – which may lead to failed crop yields,
557 while the latter affects the knowledge, access to credit, and risk perception of households who are recipient of the
558 policies.

559 **How is space included in the model?**

560 ADOPT runs on the scale of farm fields (size adjusted to the case study area). On this field scale, agricultural
561 water management decisions (adaptation) interact with rainfall variability (drought hazard). However, spatially-
562 explicit fields are used only in the initialisation phase so neighbouring farms can be identified but does not play
563 any further role: space is only represented in a spatially-implicit way, all farms (crop land) receive the same
564 amount of rain and sun, have the same soil type with a similar slope and differ only in their farm size and
565 management applied.

566 **What are the temporal resolution and extent of the model?**

567 One time step of ADOPT represents one year. The crop model part runs on a daily basis, producing maize crop
568 yield in every cropping season, but decisions by the farm households to eventually adopt new adaptation measures
569 are only made once a year. Each year, the poverty status, food security situation, and potential food aid needs of
570 all farm households are evaluated. The model runs 30 years historical baseline (+ 10 initialisation years) and 30
571 scenario years.

572 **I.iii Process overview and scheduling**

573 **What entity does what, and in what order?**

574 Every year, farm income of the households is updated with the maize harvest sold at the current market price (see
575 centre of the flowchart in Fig. A.2). This harvest depends on the farm size of the household, the maize yields
576 (defined by AquacropOS) which may be affected by a drought potentially mitigated by implemented drought
577 adaptation measures, and on the food needs of the own household (subsistence is prioritized over selling;
578 household members can die or be born (stochastically determined, based on birth and mortality rates in the study
579 area). This farm income, together with a potential (fixed) off farm income, and with farm-size-dependent farm
580 expenses, family-size-dependent household expenses, and potentially extra food expenses (if the own production
581 was not sufficient to fulfil household food needs), alters the assets of the farm household. The farm household's
582 memory of drought impacts (risk perception) is updated, and they interact (in random order) with their network
583 of neighbours exchanging information on adaptation measures.

584 Once a year, the household head decides whether they want to adopt a new drought adaptation measure. They
585 make this decision based on their memory of past drought impacts, their perception of the adaptation costs, the
586 knowledge on adaptation measures through their networks and training, and their perception of their own capacity.

587 The adoption of a new measure changes the farm management of those farmers, directly changes their wealth
 588 (implementation costs) and the farm expenses for the following years (maintenance costs), and influences crop
 589 yield and crop vulnerability to drought – thus potential farm income - during the following years.
 590

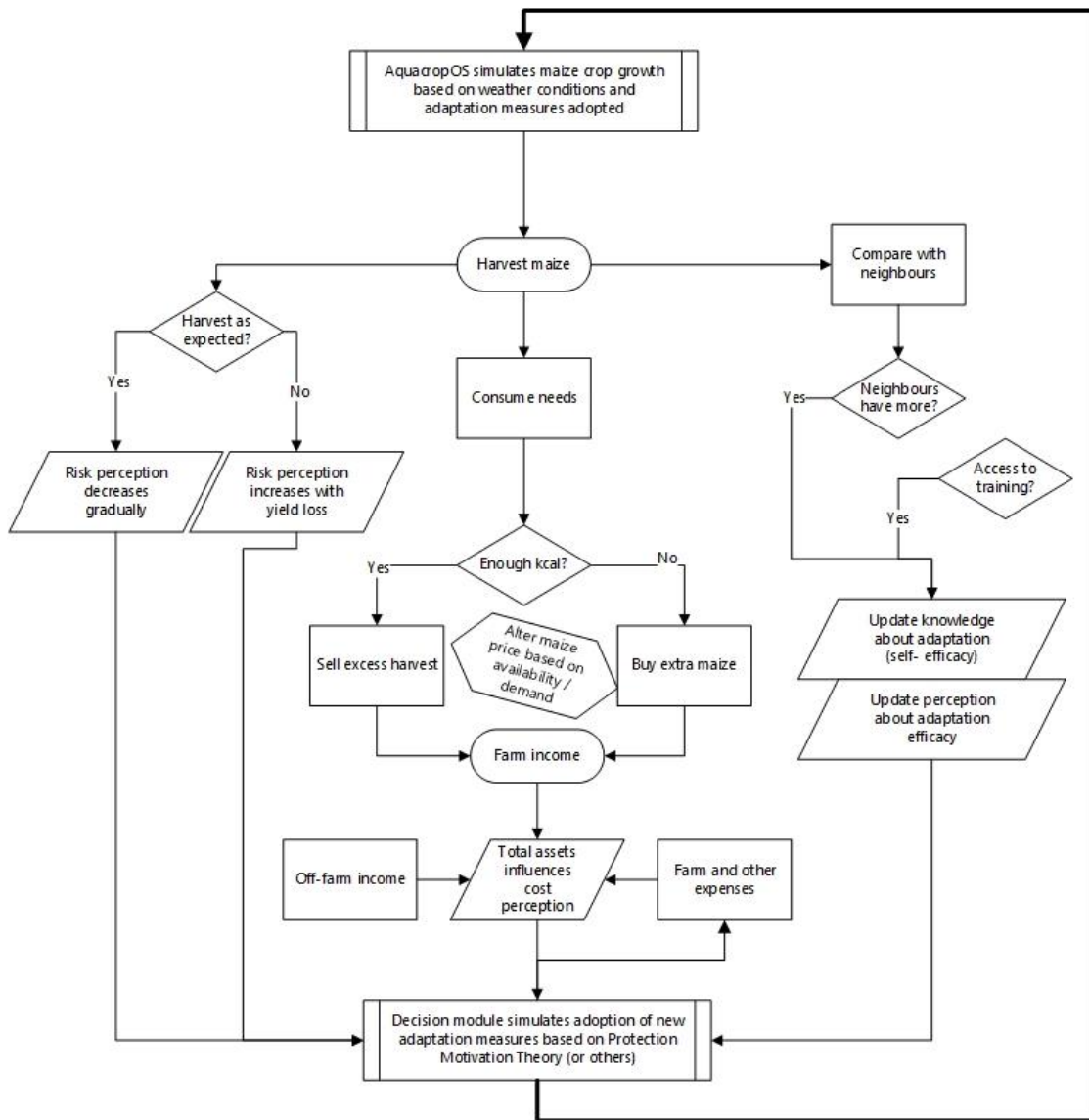


Fig.

591
 592 **Figure A2: Flowchart showing process overview**

593

594 **II. Design Concepts**

595 **II.i Theoretical and Empirical Background**

596 **Which general concepts, theories or hypotheses are underlying the model's design at the system level or at**
597 **the level(s) of the sub-model(s) ?**

598 The multi-disciplinary modelling approach of ADOPT is rooted in socio-hydrology (Sivapalan et al., 2012),
599 where the human system both influences and adapts to the changing physical environment (in this case agricultural
600 drought), and applies an agent-based approach to deal with heterogeneity in adaptive behaviour of smallholder
601 households.

602 The setup / design of the model (the drought disaster risk system) is a result of participatory concept mapping
603 with researchers and students of SEKU University, technical advisors of Kitui County Department of Water,
604 Agriculture, Livestock and Fishing, experts from SASOL foundation, and five pilot households that have example
605 farms for agricultural extension. This information informed the decision context of ADOPT.

606 **On what assumptions is/are the agents' decision model(s) based?**

607 In the first design of ADOPT, three adaptive behaviour scenarios were analysed, with increasing complexity. A
608 'business as usual' scenario with no changing drought adaptation measures was tested, characterizing the 'fixed
609 adaptation' approach. The conventional Expected Utility Theory (von Neumann and Morgenstern, 1944)
610 represents the widely-used economist assessment of choice under risk and uncertainty. Simulating bounded
611 rational rather than economic rational adaptation decisions, the Protection Motivation Theory (Rogers, 1983) is
612 used as a way to include psychological factors in the heterogeneous adaptive behaviour of smallholders.

613 Indeed, it is often stated that households' adaptive behaviour is bounded rational and embedded in the economic,
614 technological, social, and climatic context of the farmer (Adger, 2006). Knowing the risk is not enough to adapt;
615 farmers should also believe the adaptation measure will be effective, be convinced that they have the ability to
616 implement the measure, and be able to reasonably pay the costs (van Duinen et al., 2015b). Financial or knowledge
617 constraints may limit economic rational decisions. Also age, gender and education – intrinsic factors - can play a
618 role (Burton, 2014). The perceived ability to do something (Coping Appraisal) influences the decision making
619 process (Eiser et al., 2012). This coping appraisal can be subject to intrinsic factors such as education level, sources
620 of income, farm size, family size, gender, confidence and beliefs, risk-aversion, and age (Le Dang et al., 2014;
621 Okumu, 2013; Shikuku et al., 2017; Zhang et al., 2019) .

622 In order to understand the observed adaptive behaviour of smallholder households, it is critical to incorporate
623 such social-economic factors in the decision-making framework of drought adaptation models (Bryan et al., 2009,
624 2013; Deressa et al., 2009; Gbetibouo, 2009; Gebrehiwot & van der Veen, 2015; Keshavarz & Karami, 2016;
625 Lalani et al., 2016; Mandleni & Anim, 2011; O'BRIEN et al., 2007; Rezaei et al., 2017; Singh & Chudasama,
626 2017; van Duinen et al., 2015b, 2015a, 2016; Wheeler et al., 2013). After we had promising results running
627 ADOPT with the bounded rational scenario, it is assumed that farmers show a bounded rationality in the further
628 application of ADOPT.

629 **Why is a/are certain decision model(s) chosen?**

630 Analysis of the past and intended behaviour of farm households in the region provided support for the choice of
631 theory, but also showed the need to include network influencing risk perception and capacity of the households.
632 Besides helping to parameterize the model, it also helped to calibrate the influence of the different factors affecting
633 the decision making process of the farm household. Showing the effect of different assumptions about decision
634 making in the first exploration of ADOPT (M. Wens et al., 2020), and with empiric evidence on the adaptive
635 behaviour (M. L. K. Wens et al., 2021), the decision rules in ADOPT are assumed be a good enough representation
636 of the decision making process regarding drought adaptation.

637 **If the model / a sub-model (e.g., the decision model) is based on empirical data, where does the data come**
638 **from?**

639 ADOPT is designed/initialised with data from existing longitudinal household surveys (Tegemeo Institute, 2000,
640 2004, 2007, 2010) and from a fuzzy cognitive map of key informants, and parameterized/partially calibrated with
641 data from a semi-structured household questionnaire among 260 smallholder farmers Survey reports can be found
642 here:

- 643 - <https://research.vu.nl/en/publications/survey-report-kitui-kenya-expert-evaluation-of-model-setup-and-pr>
- 644 - <https://research.vu.nl/en/publications/survey-report-kitui-kenya-results-of-a-questionnaire-regardings-us>

645 **At which level of aggregation were the data available?**

646 Data from the surveys are available on individual household level.

647 **II.ii Individual Decision Making**

648 **What are the subjects and objects of decision-making? On which level of aggregation is decision-making**
649 **modelled?**

650 In ADOPT, individual farm households make individual adaptation decisions about their farm water management
651 (in the case study in Kenya: mulching, Fanya Juu terraces, drip irrigation or shallow well) to reduce their
652 production vulnerability to droughts. There are no multiple levels of decision making included.

653 **What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit**
654 **objective or have other success criteria?**

655 Farmers generally try to reduce their drought disaster risk (achieve food security, evade poverty and avoid needing
656 emergency aid) and thus try to maximise crop yields (diminish yield reduction under water-limited conditions)
657 given the capacity they have to adopt adaptation measures.

658 **How do agents make their decisions?**

659 The Protection Motivation Theory (Maddux & Rogers, 1983) (see II.i) is used to explain the decision making
660 process of the households. PMT consists of two underlying cognitive mediating processes that cause individuals
661 to adopt protective behaviours when faced with a hazard (Floyd et al., 2000): It suggests that the intention to

662 protect (in this study, the farmers' intention to adopt a new adaptation measure) is motivated by a persons' risk
 663 appraisal and the perceived options to cope with risks. The former depends on, for example, farmers' risk
 664 perception, on their own experiences with drought disasters and memory thereof, and on experiences of risk
 665 events in their social networks. The latter is related to different factors such as perceived self-efficacy (i.e. assets
 666 and sources of income, education level, and family size), adaptation efficacy (land size, adaptation measure
 667 characteristics) and adaptation costs (expenses in relation to their income) (Gebrehiwot & van der Veen, 2015;
 668 Keshavarz & Karami, 2016; van Duinen et al., 2015, 2016a). Households do not have any other objective or
 669 success criteria. A detailed description of how PMT is modelled – including the sensitivity analysis regarding the
 670 relative weights of the PMT factors - can be found in Wens et al. (2019): In ADOPT, farm households develop
 671 an intention to adapt (protect) for each potential adaptation measure (m) which changes every year (t). If a
 672 household has the financial capacity to pay for a considered measure (Stefanovi, 2015), the intention to adapt is
 673 translated into the likelihood the household will adopt this measure in the following years. (This can be influenced
 674 by having access to credit.) The actual adoption is stochastically derived from this likelihood to adopt a measure.

$$\text{IntentionToAdapt}_{t,m} = \alpha * \text{RiskAppraisal}_t + \beta * \text{CopingAppraisal}_{t,m}$$

675
 676 Although Stefanovi (2015), Van Duinen et al. (2015a), and Keshavarz and Karami (2016) have found positive
 677 relationships between the factors of PMT and observed protective behaviour, a level of uncertainty exists related
 678 to the relative importance of risk appraisal and coping appraisal in the specific context of smallholder households'
 679 adaptation decisions in semi-arid Kenya. Therefore, the α and β parameters were introduced as weights for the
 680 two cognitive processes. To address the associated uncertainty, they were widely varied ($\alpha, \beta \in [0.334:0.666]$) in
 681 a sensitivity analysis.

682 Risk appraisal is formed by combining the perceived risk probability and perceived risk severity, shaped by
 683 rational and emotional factors (Deressa et al., 2009, 2011; Van Duinen et al., 2015b). Whereas risk perception is
 684 based in part on past experiences, several studies have suggested that households place greater emphasis on recent
 685 harmful events (Gbetibouo, 2009; Rao et al., 2011; Eiser et al., 2012). To include this cognitive bias, risk appraisal
 686 is seen as a sort of subjective, personal drought disaster memory, defined as follows (Viglione et al., 2014):

$$\begin{aligned} \text{RiskAppraisal}_t &= \text{RiskAppraisal}_{t-1} + (\text{Drought}_t * \text{Damage}_t) \\ &\quad - 0.125 * \text{RiskAppraisal}_{t-1} \text{ with } \text{Damage}_t \\ &= 1 - \exp(-\text{harvestloss}_t) \end{aligned}$$

687
 688 The drought occurrence in year t is a binary value with a value of 1 if the SPEI-3 value falls below -1. The disaster
 689 damage of a household is related to their harvest loss during the drought year, which is defined as the difference
 690 between their current and average harvest over the last 10 years.

691 Coping Appraisal represents a households' subjective "ability to act to the costs of a drought adaptation measures,
 692 given the adaptation measures' efficiency in reducing risk" (Stefanovi, 2015; Van Duinen et al., 2015a). It is a
 693 combination of the households' self-efficacy, adaptation efficacy of the measure, and its adaptation costs:

$$CopingAppraisal_{t,m} = \gamma * SelfEfficacy_t + \delta * AdaptationEfficacy_{t,m} + \varepsilon * (1 - Adaptationcosts_t)$$

694

695 Although Stefanovi (2015), Van Duinen et al. (2015b), and Keshavarz and Karami (2016) quantified the
 696 relationships between the factors driving the subjective coping appraisal of individuals, a level of uncertainty
 697 remains related to the relative importance of these drivers in the context of smallholder households' adaptation
 698 decisions in semi-arid Kenya. Therefore, weights (γ , δ , $\varepsilon \in [0.25:0.50]$) were introduced and varied in a sensitivity
 699 analysis using different ADOPT model runs.

700 The Adaptation Costs of the possible measures are expressed in terms of a percentage of the households' assets.
 701 The Adaptation Efficacy is calculated as the percentage of yield gain per measures compared to the current yield.
 702 This can be influenced by access to extension services (which gives an objective yield gain based on future climate
 703 rather than an estimate based on current practices of neighbours)

704 Self-efficacy is assumed to be influenced by education level (capacity), household size (labour force), age and
 705 gender; all social factors found to influence risk aversion and adaptation decision (Oremo, 2013; Charles et al.,
 706 2014; Tongruksawattana, 2014; Muriu et al., 2017).

707 **Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes,**
 708 **how?**

709 Exogenous factors influencing adaptation decisions in ADOPT include the climate and the policy context in which
 710 households exists. Drought (a feature of the climate context) induced crop losses steer a households' perception
 711 of the drought disaster risks they face (Risk Appraisal). For example, experiences of historical droughts or
 712 receiving early warnings about upcoming drought affects individuals' evaluation of drought disaster risk, leading
 713 to a personal drought disaster risk judgement (e.g. Keshavarz et al., 2014; Singh & Chudasama, 2017). Besides,
 714 access to extension services (a feature of the climate context) can have profound effect on whether or not
 715 individuals take proactive action (Kitinya et al., 2012; Shikuku et al., 2017). Endogenous factors, as explained
 716 above, include age, household size, education level, maize yield variability and assets (and the potential access to
 717 credit market).

718 **Do spatial aspects play a role in the decision process?**

719 Farmer networks (connections with neighbours) exist, and information is passed through this social network.

720 **Do temporal aspects play a role in the decision process?**

721 Yes, risk memory is based on the crop yield variability of the accumulated past years and gives farm households
 722 an expectation about the upcoming crop yield.

723 **Do social norms or cultural values play a role in the decision-making process?**

724 No (only implicitly included, see II.ix)

725 **To which extent and how is uncertainty included in the agents' decision rules ?**

726 No

727 **II.iii Learning**

728 **Is individual learning included in the decision process? How do individuals change their decision rules over**
729 **time as consequence of their experience?**

730 Decision rules follow the PMT and are thus fixed, but some rules differ among type of households. Households
731 that do not regularly receive extension services, are limited to only implement measures that their neighbours
732 have installed as they are not aware of the existence of others. Besides, farmers who receive training will form
733 their perception about the adaptation efficacy in a more objective way (as they have knowledge of average yield
734 results under the adaptation measures while other farmers estimate this based on yield of their peers with such
735 measure).

736 **Is collective learning implemented in the model?**

737 No

738 **II.iv Individual Sensing**

739 **What endogenous and exogenous state variables are individuals assumed to sense and consider in their**
740 **decisions? Is the sensing process erroneous?**

741 Households are aware of their assets, past yields, income sources and their stability, and household food needs
742 (Fig. A1). Following the socio-hydrologic setup of the model, households with bounded rational behaviour are
743 embedded in and interact with their social and natural environment. Changes in rainfall patterns during the
744 growing season will change households' risk perception through fluctuations in crop yield; drought memory will
745 influence the adaptive behaviour of these households. Besides, there is a diffusion of technology due to
746 interactions and knowledge exchanges among farm households as discussed above.

747 **What state variables of which other individuals can an individual perceive?**

748 Households know their own but also their neighbours' current yields and management practices. They make
749 assumptions about the adaptation efficacy based on this.

750 **What is the spatial scale of sensing?**

751 Individual sensing happens on household level, but also through the individual social network that the farmers
752 have, containing 3 to 30 other farmers.

753 **Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply**
754 **assumed to know these variables?**

755 Households can get information about early warnings and through extension training. Households also have a
756 simulated information transfer moment with the farmers in their neighbourhood to exchange information on risk
757 and yields.

758 **Are the costs for cognition and the costs for gathering information explicitly included in the model?**

759 No

760 **II.v Individual Prediction**

761 **Which data uses the agent to predict future conditions?**

762 By extrapolating from historical yield experiences, farmers have expectations about their maize yield every year.
763 If an early warning system is in place, farmers know about upcoming droughts that can influence their crop yield.

764 **What internal models are agents assumed to use to estimate future conditions or consequences of their**
765 **decisions?**

766 Households receiving extension services have knowledge about the average (future) yield gain of adopting a new
767 adaptation measure, which will influence their coping appraisal.

768 **Might agents be erroneous in the prediction process, and how is it implemented?**

769 Households without this access to training will predict the yield gain based on the extra yield of their neighbours
770 who have already adopted the considered adaptation measure.

771 **II.vi Interaction**

772 **Are interactions among agents and entities assumed as direct or indirect?**

773 In ADOPT, households interact with their neighbours, shaping risk awareness and response attitude (Nkatha,
774 2017; Okumu, 2013; van Duinen et al., 2016). Such networks can enhance social learning and knowledge spill
775 over, which influences people's adaptation intention and choice of specific measures (Below et al., 2010;
776 Tongruksawattana, 2014). Smallholder households learn from the other households in their social network about
777 the implementation and benefits of drought adaptation measure through neighbouring households' (Below et al
778 2010; Shikuku 2017). In ADOPT, exchanges with neighbours shape risk perception – the individual perception
779 moves in the direction of the social network average – and also shape perceived adaptation effectivity. Moreover,
780 households with no access to extension can only adopt measures already implemented by neighbours.

781 **On what do the interactions depend?**

782 Households are either more self-oriented, discussing matters with 10 neighbours, or group-oriented, sharing
783 knowledge within a group / collective of 30 neighbouring households.

784 Spatial distance (neighbourhood) at initialisation is the key driver for networks; it is assumed that s(he) would
785 not walk more than 5km to reach people in her/his network.

786 **If the interactions involve communication, how are such communications represented?**

787 Communication is not explicitly modelled.

788 **If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network
789 imposed or emergent?**

790 No coordination network exists.

791 **II.vii Collectives**

792 **Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? How
793 are collectives represented?**

794 No, no fixed collectives exist as the social networks the agents have, are individual in nature.

795 **II.viii Heterogeneity**

796 **Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?**

797 Household agents are heterogeneous in terms of state variables (i.e. farm size, household size, assets), and differ
798 in access to credit market, extension services and early warning beneficiaries, changing their adaptive behaviour
799 (Asfaw et al., 2017; Okumu, 2013; Shikuku et al., 2017)

800 **Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects
801 differ between the agents?**

802 Okumu (2013), Shikuku (2017), among others, found that state variables such as age, beliefs, gender, education
803 of the household head, and the household size have significant effects on their risk attitude. These factors are
804 included in the model application of the Protection Motivation Theory through the self-efficacy factor.

805 **II.ix Stochasticity**

806 **What processes (including initialization) are modelled by assuming they are random or partly random?**

807 The likelihood to adopt a measure of a household is directly derived from the intention to adapt of the measure
808 with the highest intention for that household. This is stochastically transferred into an actual decision whether or
809 not to adopt the measure. For every time step of the simulation, a random number between 0-1 is drawn for each
810 household; if this is lower than their adaptation intention (also between 0-1) and the household is able to pay for
811 the measure, then the household adopts it. This probabilistic way of looking at adaptation intention and the
812 stochastic step to derive the actual decisions allow to account for non-included factors introducing uncertainty in
813 adaptive behaviour such as conservatism, social / cultural norms, physical health, ambitiousness etc. of the
814 households. Moreover, also a stochastic perturbation (multiplied with a random number with average 1 and SD

815 0.1) is added to the maize yield per farm as calculated through AquacropOS. This additional heterogeneity-
816 inducing step is done to include effects of pests and diseases on the income and food security of farming
817 households.

818 **II.x Observation**

819 **What data are collected from the ABM for testing, understanding and analysing it, and how and when are**
820 **they collected?**

821 The adoption of adaptation measures and their effect on the total crop production (and food stock on the market)
822 and individual household wealth are tracked over the simulated years.

823 **What key results, outputs or characteristics of the model are emerging from the individuals?**

824 Drought disaster risk (the annual average of impacts over the run period) - expressed in terms of average annual
825 poverty rate, level of food security and total emergency aid needs - is emerging from the model. They are defined
826 based on the socio-economic conditions of individual farm households.

827 **III. Details**

828 **III.i Implementation**

829 **How has the model been implemented?**

830 The model is coded in R, which is able to link the two sub models in Netlogo (the adaptive behaviour sub model)
831 and MATLAB (AquacropOS).

832 **Is the model accessible, and if so, where?**

833 No(t) yet

834 **III.ii Initialization**

835 **What is the initial state of the model world, i.e., at time $t=0$ of a simulation run?**

836 At the initial stage, households and their characteristics are randomly created based on the mean and standard
837 deviation (Table A1) derived from the household dataset, obtained from a survey on agricultural drought disaster
838 risk with smallholders in the case study area (Wens, 2019). Income off farm is linearly related to the household
839 size, education level and negatively related to the farm size. Food and non-food expenditures are linearly related
840 to the household size. Farm expenditures are linearly related to the farm size.

841 **Table A1: 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
Food-needs	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
Network	Neighbouring farmers creating the social network of the farmer	10-30

842

843 **Is initialization always the same, or is it allowed to vary among simulations?**

844 In ADOPT, multiple climate change scenarios and policy scenarios were initialised – this changed the exogeneous
 845 variables in the model. Moreover, each initialization creates another synthetic agent set based on the average
 846 household characteristics. Besides, a sensitivity analysis is done to evaluate assumptions on the relative weights
 847 of the PMT factors (II.ii). Each combination of climate and policy scenario is run 12 times (3 possible α ; 4
 848 possible combinations of $\gamma, \delta, \varepsilon$) to account for the endogenous variability and uncertainty.

849 **Are initial values chosen arbitrarily or based on data?**

850 The initialisation values are based on observed household data. Survey data includes a short questionnaire among
 851 employees of the Kenyan national disaster coordination units (n=10), semi-structured expert interviews (n=8)
 852 with NGOs, governmental water authorities and pioneer farmers in the Kitui district in Kenya, and an in-depth
 853 questionnaire among 250 smallholder farmers in the central Kitui. Extra information is derived from household
 854 surveys of 2000, 2004, 2007 and 2010, conducted by the Tegemeo Agricultural Policy Research Analysis
 855 (TARAA) Project of the Tegemeo Institute. Besides, the model initialization draws heavily from reports of CIAT
 856 (CIAT & World Bank, 2015), FAO (Rapsomanikis, 2010), IFPRI (Erenstein et al., 2011) and the government of
 857 Kenya (Kitui County Integrated report 2013-2017, 2017), CCAFS (CCAFS, 2015), and from research (e.g.,
 858 Muhammad et al., 2010).

859 **III.iii Input Data**

860 **Does the model use input from external sources such as data files or other models to represent processes**
861 **that change over time?**

862 The daily weather conditions from 1980-2010 (from CHIRPS and CFSR) is used as input time series; for the
863 future climate scenarios, the same data but with temperature and/is used.

864 Besides, survey data on household behaviour and drought risk context are used. Raw reporting can be found in:

865 • Wens, M. (2019). Survey report Kitui, Kenya: Results of a questionnaire regarding subsistence
866 farmers' drought risk and adaptation behaviour.

867 <https://research.vu.nl/ws/portalfiles/portal/98864069/MissionRapport.pdf>

868 • Wens, M (2018) Survey report Kitui, Kenya: Expert evaluation of model setup and preparations of
869 future fieldwork <https://research.vu.nl/ws/portalfiles/portal/98863978/MissionRapport2018.pdf>

870 **Where does data come from? How is it collected? What is the level of available data? How is it structured?**

871 Data (also discussed in Wens et al. 2021) is collected in the field using a multi-method data survey approach
872 (key informant interviews, fuzzy cognitive map, household questionnaire and choice experiment). This data is
873 used to design the model, to validate the use of PMT, to initialise the agent set and to calibrate model outputs.

874 **What are the variables, entities and classes available in data? What do they represent?**

875 A full set of behavioural factors were evaluated through the household questionnaire, and these were linked to
876 their actual behaviour and to their behavioural intentions, as well as to the results of the choice experiment
877 investigating future behaviour (Wens et al. 2021). Besides, socio-economic and farm characteristics were
878 questioned.

879 **How are data selected to form the agent entities? How is agent population generated and synthesized?**

880 As discussed above, the data is used to create a representative set of agents. Household variable means and
881 standard deviations were used to create distribution functions and a synthetic agent set was created based on
882 random draws from these functions. Moreover, correlation between different variables were maintained.

883 **What are the relationships and patterns that exist in data?**

884 As discussed above, relationship between household income and household head education level or farm size
885 exist. Next to correlations between socio-economic or agricultural characteristics, correlations between
886 psychological factors and actual or prospective adaptation decisions were investigated and used to design the
887 behavioural module of ADOPT.

888 **III.iv Sub-models**

889 **What, in detail, are the sub-models that represent the processes listed in ‘Process overview and**
 890 **scheduling’?**

891 The FAO crop-water model AquacropOS (coded in MATLAB© by Tim Foster (Foster et al., 2017)) calculates
 892 seasonal crop production, based on hydro-climatologic conditions provided by the climate data and based on the
 893 agricultural management of the households. The agent-based model in which farming households decide on their
 894 drought adaptation measures, is coded in Netlogo®, a language specialized in ABMs. This contains the -making-
 895 decision module, which is a model-application of the Protection Motivation theory as explained in section II.i.
 896 More detailed explanation about how this is done can be found in Wens et al 2020.

897 **How were sub models designed or chosen, and how were they parameterized and then tested?**

898 AquacropOS was applied parameterized and calibrated following Ngetich (2011) and Omyo (2015), who both
 899 analysed and approved the functioning of this model to simulate maize yield under different climates in Kenya.
 900 The decision sub-model is described above in the sections about decision-making and theoretical foundations
 901 (II.ii). A more detailed description can be found in Wens et al 2020.

902 **What are the model parameters, their dimensions and reference values?**

903 For AquacropOS, Table A3 and A4 give an overview of the parameters that are used. For the decision-making
 904 module, Table A2 gives an overview of the factors used.

905 **Table A2: Initialisation parameters for the behavioural module in ADOPT**

Factor	Explanation of the PMT factors
Current Yield	Average yield of last 5 years
Potential Yield	Expected / perceived yield when adopting a new adaptation measure Either based on yield of neighbours with that measure or on training info
Adaptation costs	Perception of the costs of new measures as percentage of assets
Knowledge-measures	1 if attending trainings, else the percentage of people in network with measure
Risk perception	Drought memory, 1 if last harvest there was 0 yield, 0 if never impacted
Adaptation efficacy	Yield gain as percentage of current yield, based on potential yield
Self – efficacy	Belief in own capacity, based on gender, age, HH size and access to training
Adaptive capacity	Product of self-efficacy, adaptation efficacy and -1 * adaptation costs
Adaptation intention	Product of adaptive capacity and risk perception, 0 if one of the underlying factors is 0 or if assets are smaller than costs of measure

906

907 **Table A3: 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 (%)

908

909 **Table A4: Crop parameters for maize AQUACROPOS in ADOPT**

910	Value	Crop parameters for AquacropOS
911	3	: Crop Type (1 = Leafy vegetable, 2 = Root/tuber, 3 = Fruit/grain)
912	1	: Planting method (0 = Transplanted, 1 = Sown)
913	1	: Calendar Type (1 = Calendar days, 2 = Growing degree days)
914	0	: Convert calendar to GDD mode if inputs are given in calendar days (0 = No; 1 = Yes)
915	16/03	: Planting Date (dd/mm)
916	31/08	: Latest Harvest Date (dd/mm)
917	5	: Growing degree/Calendar days from sowing to emergence/transplant recovery
918	40	: Growing degree/Calendar days from sowing to maximum rooting
919	80	: Growing degree/Calendar days from sowing to senescence
920	90	: Growing degree/Calendar days from sowing to maturity
921	40	: Growing degree/Calendar days from sowing to start of yield formation
922	5	: Duration of flowering in growing degree/calendar days (-999 for non-fruit/grain crops)
923	65	: Duration of yield formation in growing degree/calendar days
924	3	: Growing degree day calculation method
925	8	: Base temperature (degC) below which growth does not progress
926	30	: Upper temperature (degC) above which crop development no longer increases
927	1	: Pollination affected by heat stress (0 = No, 1 = Yes)
928	35	: Maximum air temperature (degC) above which pollination begins to fail
929	40	: Maximum air temperature (degC) at which pollination completely fails
930	1	: Pollination affected by cold stress (0 = No, 1 = Yes)
931	10	: Minimum air temperature (degC) below which pollination begins to fail
932	5	: Minimum air temperature (degC) at which pollination completely fails
933	1	: Transpiration affected by cold temperature stress (0 = No, 1 = Yes)
934	12	: Minimum growing degree days (degC/day) required for full crop transpiration potential
935	0	: Growing degree days (degC/day) at which no crop transpiration occurs
936	0.3	: Minimum effective rooting depth (m)
937	0.8	: Maximum rooting depth (m)

938 1.3 : Shape factor describing root expansion

939 0.0105 : Maximum root water extraction at top of the root zone (m³/m³/day)

940 0.0026 : Maximum root water extraction at the bottom of the root zone (m³/m³/day)

941 6.5 : Soil surface area (cm²) covered by an individual seedling at 90% emergence

942 37000 : Number of plants per hectare

943 0.89 : Maximum canopy cover (fraction of soil cover)

944 0.1169 : Canopy decline coefficient (fraction per GDD/calendar day)

945 0.2213 : Canopy growth coefficient (fraction per GDD)

946 1.05 : Crop coefficient when canopy growth is complete but prior to senescence

947 0.3 : Decline of crop coefficient due to ageing (%/day)

948 33.7 : Water productivity normalized for ET₀ and CO₂ (g/m²)

949 100 : Adjustment of water productivity in yield formation stage (% of WP)

950 50 : Crop performance under elevated atmospheric CO₂ concentration (%)

951 0.48 : Reference harvest index

952 0 : Possible increase of harvest index due to water stress before flowering (%)

953 7 : Coefficient describing positive impact on harvest index of restricted vegetative growth during yield formation

954 3 : Coefficient describing negative impact on harvest index of stomatal closure during yield formation

955 15 : Maximum allowable increase of harvest index above reference value

956 1 : Crop Determinacy (0 = Indeterminant, 1 = Determinant)

957 50 : Excess of potential fruits

958 0.02 : Upper soil water depletion threshold for water stress effects on affect canopy expansion

959 0.20 : Upper soil water depletion threshold for water stress effects on canopy stomatal control

960 0.69 : Upper soil water depletion threshold for water stress effects on canopy senescence

961 0.80 : Upper soil water depletion threshold for water stress effects on canopy pollination

962 0.35 : Lower soil water depletion threshold for water stress effects on canopy expansion

963 1 : Lower soil water depletion threshold for water stress effects on canopy stomatal control

964 1 : Lower soil water depletion threshold for water stress effects on canopy senescence

965 1 : Lower soil water depletion threshold for water stress effects on canopy pollination

966 1 : Shape factor describing water stress effects on canopy expansion

967 2.9 : Shape factor describing water stress effects on stomatal control

968 6 : Shape factor describing water stress effects on canopy senescence

969 2.7 : Shape factor describing water stress effects on pollination

Appendix B: Adoption rates of adaptation measures

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	No Change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	50.2%	47.8%	45.6%	42.1%	35.9%	38.5%
<i>Proactive</i>	83.8%	83.6%	89.4%	90.1%	90.7%	88.1%
<i>Prospective</i>	100%	100%	100%	100%	100%	100%
Fanya Juu	No Change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	71.1%	70.9%	69.1%	68.8%	60.7%	63.3%
<i>Proactive</i>	87.2%	88.1%	90.7%	90.9%	91.9%	90.1%
<i>Prospective</i>	93.7%	93.5%	94.7%	94.8%	95.1%	94.9%
Well	No Change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	9.4%	9.6%	9.4%	9.2%	9.1%	9.0%
<i>Proactive</i>	11.7%	12.7%	13.4%	12.0%	12.1%	11.4%
<i>Prospective</i>	79.4%	82.6%	92.1%	92.9%	95.0%	91.1%
Irrigation	No Change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	3.7%	3.7%	3.5%	3.4%	3.3%	3.4%
<i>Proactive</i>	5.2%	5.6%	5.6%	5.3%	5.2%	4.8%
<i>Prospective</i>	48.7%	59.6%	73.3%	75.8%	82.0%	71.8%

980 Table B2 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).

<i>mulch</i>	No Change	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	0	-2.5%	-4.6%	-8.1%	-14.3%	-11.6%
<i>Proactive</i>	33.7%	33.4%	39.3%	39.9%	40.5%	38.0%
<i>Prospective</i>	49.4%	49.4%	49.8%	49.8%	49.8%	49.8%
<i>EWS</i>	18.0%	19.7%	18.8%	13.5%	-4.5%	1.2%
<i>transfer</i>	23.2%	14.4	19.6%	24.6%	23.8%	18.4%
<i>Credit2</i>	19.5%	16.6%	14.7%	8.5%	5.4%	9.1%
<i>training</i>	30.1%	27.6%	24.9%	20.4%	10.8%	15.1%

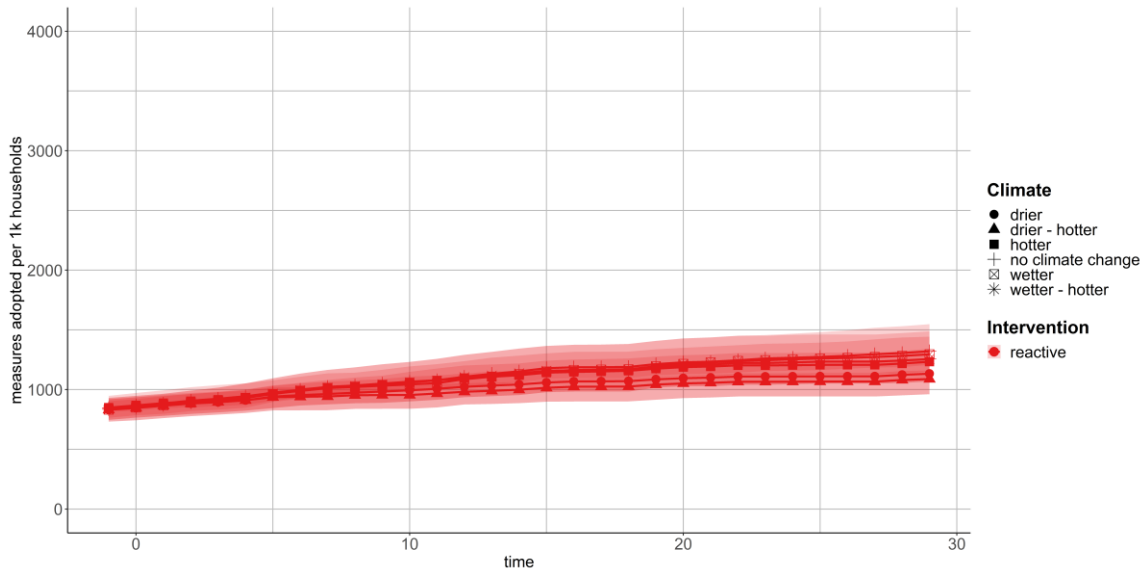
<i>Fanya Juu</i>	NC	Wet	Wet Hot	Hot	Dry Hot	Dry
<i>Reactive</i>	0%	-0.2%	-2%	-2.3%	-10.3%	-7.7%
<i>Proactive</i>	16.2%	17.0%	19.6%	19.8%	20.8%	19.1%
<i>Prospective</i>	22.6%	22.4%	23.6%	23.8%	24.1%	23.8%
<i>EWS</i>	8.2%	9.2%	8.5%	6.0%	-0.2%	1.3%
<i>transfer</i>	9.0%	5.9%	6.9%	10.3%	10.1%	8.4%
<i>Credit2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

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

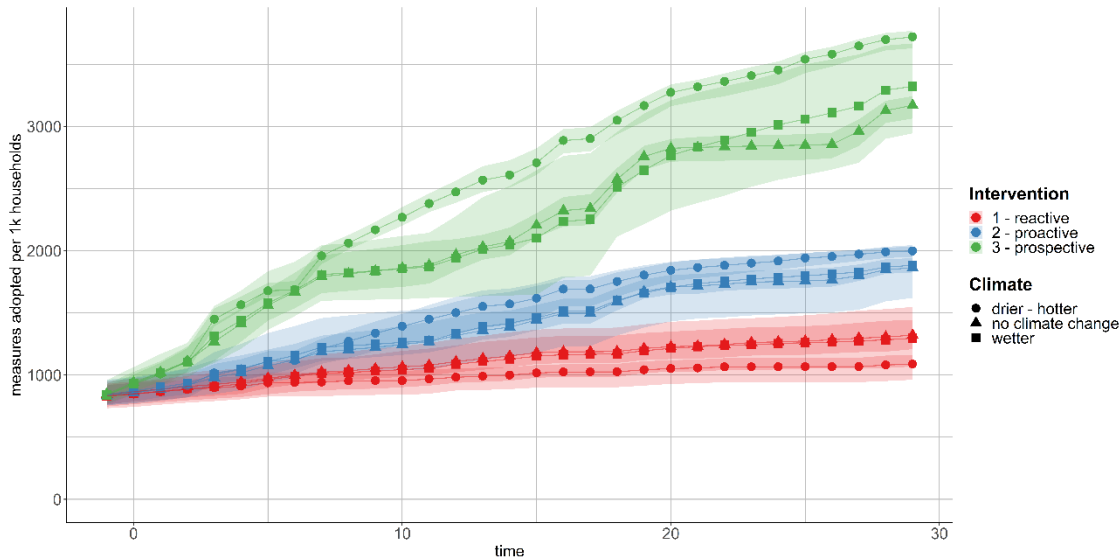
<i>Irrigation</i>	NC	Wet	Wet Hot	Hot	DRY	Dry Hot
<i>Reactive</i>	0%	0%	-0.1%	-0.3%	-0.4%	-0.3%
<i>Proactive</i>	1.5%	1.9%	1.9%	1.6%	1.5%	1.2%
<i>Prospective</i>	45.1%	56.0%	69.6%	72.1%	78.3%	68.1%
<i>EWS</i>	1.3%	1.6%	1.6%	1.4%	0.5%	0.7%
<i>transfer</i>	0.6%	0.3%	0.1%	-0.2%	-0.4%	-0.4%
<i>Credit2</i>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

% change tov 1343 adopted measures under NC reactive

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



985 **Figure B1:** Total amount of measures adopted per 1000 initialized households under the reactive scenario, averaged over all runs. The shaded area indicates the uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households. Year 0 initiates policy drought risk reduction interventions (indicated with different line colours).



990 **Figure B2:** Total amount of measures adopted per 1000 initialized households under the three intervention scenarios and three climate change scenarios, averaged over all runs. The shaded area indicates the uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households. Year 0 initiates policy drought risk reduction interventions (indicated with different line colours).

Author contribution

M. W. took lead in model development, scenario development and writing the manuscript. T.V. assisted model development,
995 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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