## Farmers facing droughts

Wens, Marthe Linda Kris

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VRIJE UNIVERSITEIT

# FARMERS FACING DROUGHTS

## CAPTURING ADAPTATION DYNAMICS IN DISASTER RISK MODELS

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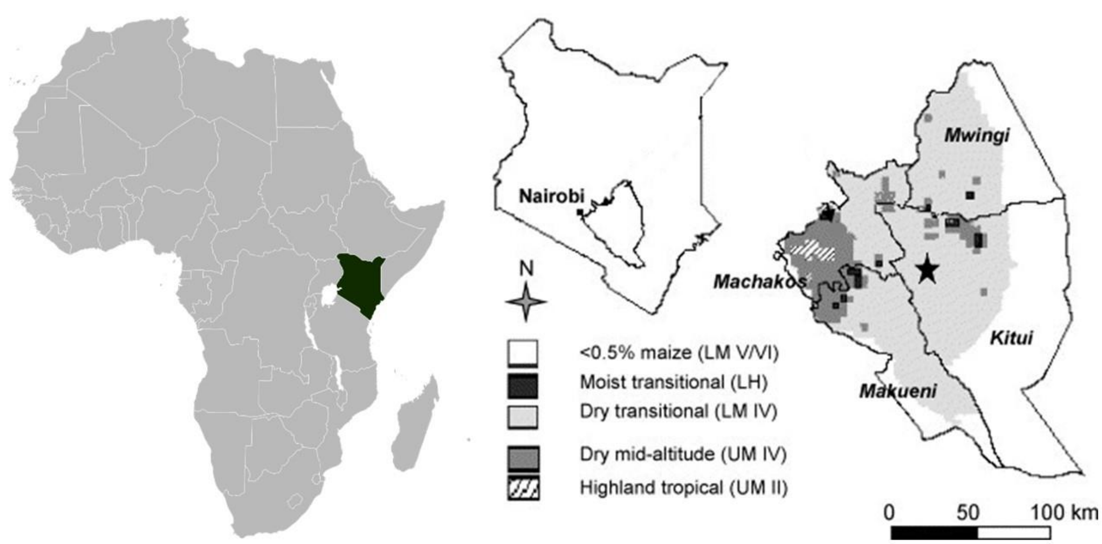
# *BOEREN BIEDEN HET HOOFD AAN DROOGTES*
# DE INTEGRATIE VAN MENSELIJK ADAPTIEF GEDRAG IN DROOGTE RISICO ANALYSES

Droogte is een hardnekkig en kostelijk gevaar dat gevolgen heeft voor mens en milieu. Naarmate de klimaatverandering en de sociaaleconomische ontwikkeling verder toenemen, wordt verwacht dat het droogterisico in veel delen van de wereld zal toenemen. De unieke kenmerken van droogteperiodes - namelijk hun langzame aanvang en grote omvang in ruimte en in tijd - maken het een uitdaging om het droogterisico nauwkeurig in te schatten. In dit proefschrift reflecteer ik op hoe bestaande studies het droogterisico hebben gemodelleerd en benadrukt de mogelijkheid om menselijk adaptief gedrag (bereidheid en/of mogelijkheden tot aanpassing van het gedrag) expliciet mee te nemen in droogterisicobeoordelingen. Een betrouwbare beoordeling van het huidige en toekomstige droogterisico is van cruciaal belang voor de ontwikkeling van duurzaam beheer van water- en landbouwhulpbronnen. Eerdere modellen zijn echter grotendeels gebaseerd op hydrologische modellen en missen de menselijke component. Een dergelijke focus op de natuurlijke processen van de watercyclus laat de tweerichtingsfeedback tussen het watersysteem en de dynamiek van menselijke activiteiten achterwege. Dit samenspel kan echter de evolutie van toekomstige droogterisico's beïnvloeden: enerzijds hebben adaptatiebeslissingen (i.e. beslissingen over het nemen van adaptatiemaatregelen ter vermindering van het droogterisico) invloed op het risico en anderzijds zal ook de manifestatie van het risico (het ervaren van droogte-impact) de opkomende adaptatiebeslissingen beïnvloeden.

In dit proefschrift stel ik dat de toevoeging van dergelijk menselijk adaptief gedrag, een noodzakelijke stap is om de evolutie van droogterisico goed te kunnen modelleren. Elke individuele keuze heeft het vermogen om de verspreiding, omvang en effecten van een droogte te beïnvloeden. Het begrijpen van hoe mensen adaptatiebeslissingen nemen en waarom die verschillen van persoon tot persoon, is cruciaal: Het kan helpen bij beleidsbeslissingen over het ondersteunen van individuele adaptatiebeslissingen, voor het anticiperen op hulpbehoeften tijdens droogterampen en voor het evalueren van strategieën voor het verminderen van risico's bij droogte. Ik heb aangetoond hoe de dynamiek van menselijk adaptief gedrag kan worden geïntegreerd in risicobeoordelingen van droogte, om zo de dynamische aard van kwetsbaarheid voor droogte correcter weer te geven. Om een tastbaar, praktisch voorbeeld te geven, richt het hier gepresenteerde onderzoek zich op de implementatie van agrarische waterbeheermaatregelen van kleine boeren.

Dit proefschrift focust op de situatie Kitui, Makueni and Machakos, drie semi-aride districten in Zuidoost-Kenia. Droogte is er de belangrijkste oorzaak is van voedsel- en inkomens-tekorten. In dit landelijke gebied zijn de meeste huishoudens afhankelijk van zelfvoorzienende landbouw. Klimaatverandering heeft er de frequentie en intensiteit van periodes van droogte in de afgelopen twee decennia doen toenemen, waardoor de productiviteit van de landbouwsector sterk op de proef wordt gesteld. De verhoogde variabiliteit in neerslag en temperatuur heeft er het huidige aanpassingsvermogen overschreden. Veel kleinschalige boeren zijn niet meer in staat om de gevolgen van de droogte op te vangen. Ze hebben nauwelijks de capaciteit om maatregelen te nemen om zich te beschermen tegen droogte. Dit verhoogt de voedselonzekerheid en het armoedecijfer, en resulteert in hoge financiële hulpnoden wanneer een droogteramp zich voordoet.



**Het gebruik van op-agent-gebaseerde modellen**

Lopend onderzoek om de sociaal-hydrologische feedback tussen menselijke adaptatiebeslissingen en het risico op droogte in de landbouw vast te leggen, heeft "op-agent-gebaseerde modellen" (ABM) op de voorgrond gebracht. Dit proefschrift biedt een gekoppeld modelleringsraamwerk om de wisselwerking tussen menselijke adaptatiebeslissingen en de dynamieken van droogtegevaar, blootstelling en kwetsbaarheid beter weer te geven. Ik onderzocht hoe dergelijke ABM's kunnen worden gebruikt om individueel adaptief gedrag te integreren, enrkt hoe het samenbrengen van biofysische, landgebruiks- en sociaaleconomische modellen past binnen een op agenten-gebaseerde opzet. Het belang van het meenemen van de interacties tussen mensen en droogte, een zogeheten sociohydrologische opzet, werd in de verf gezet. Dit zorgt ervoor dat de co-evolutie van menselijke adaptatiebeslissingen en droogterampen nauwkeuriger kan worden weergegeven. Verder werden ook theorieën over menselijk gedrag uitgelegd. Dit kan helpen om de keuze over factoren die invloed hebben op het menselijk beslissingsgedrag (bijvoorbeeld eerdere droogte-ervaringen, adaptaties-kosten, individuele risicoaversie en beschikbare financiële middelen) bij de modelopzet te verantwoorden.

**Empirische informatie over het beslissingsproces**

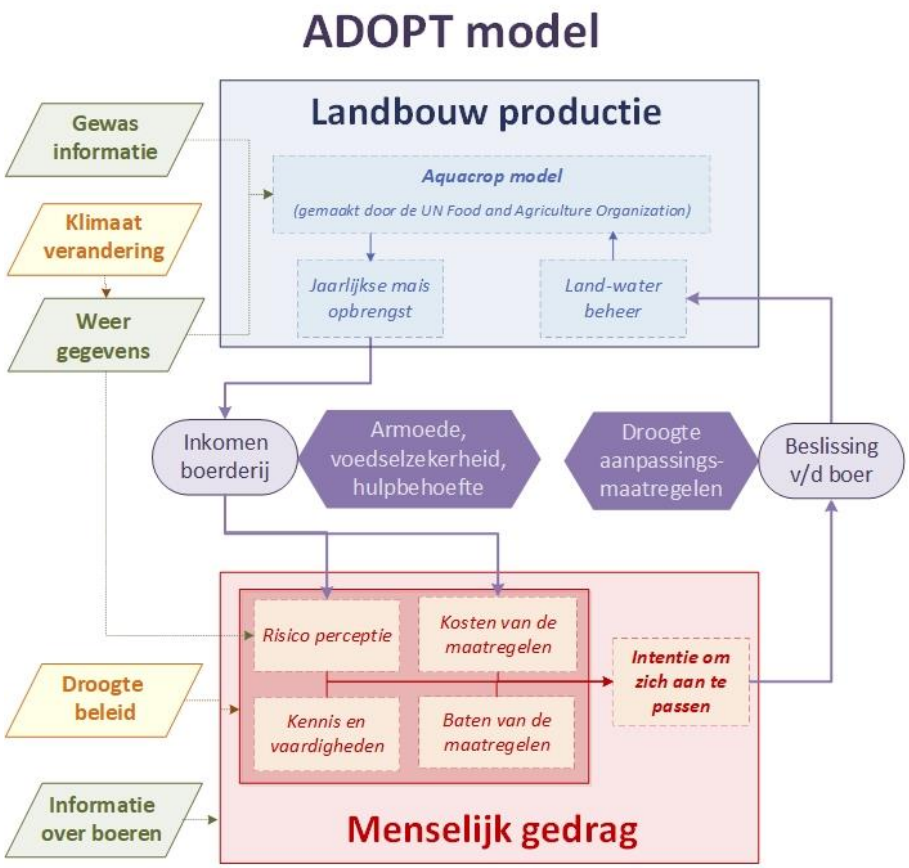
Zoals benadrukt in het modelleringsraamwerk, is gedetailleerde kennis nodig van wat mensen motiveert om adaptatiemaatregelen te installeren, wanneer men dergelijk adaptief gedrag wil opnemen in droogtemodellen. Daarom heb ik meerdere gegevensverzamelingsactiviteiten uitgevoerd onder kleine agrariërs in Kitui en andere Kenyaanse en Oost-Afrikaanse belanghebbenden. Dit zorgde voor empirisch bewijs over het adaptieve gedrag van kleine agrariërs zowel onder vroegere omstandigheden als onder mogelijk toekomstig overheidsbeleid. Ik maakte gebruik van meerdere methoden en combineer participatieve, elementaire statistische en geavanceerde econometrische benaderingen om de drijfveren en belemmeringen die van invloed zijn op adaptatiebeslissingen te beschrijven. Ook werden de voorkeuren van mensen voor beleidsstrategieën voor het verminderen van droogterisico's getest.

Ik ontdekte dat wantrouwen in voorspellingen (-29%) en een sterk geloof in God (58%) barrières voor adaptatie bleken te zijn. Daarnaast bleken lid zijn van een boerenassociatie (+38%) en het al uitgevoerd hebben van andere adaptatiemaatregelen (+44%) de intentie om nieuwe maatregelen te nemen, te stimuleren. Het belang van verschillende componenten van bestaande gedragstheorieën werd bevestigd: risicobeoordeling, sociale norm, zelfeffectiviteit, adaptatiekosten en de effectiviteit van de maatregelen beïnvloeden het adaptieve gedrag onder droogterisico aanzienlijk. Geen van de eerder beschreven gedragstheorieën kon het waargenomen gedrag echter volledig verklaren. Bovendien toonde ik door middel van een keuze-experiment aan dat beleidsacties een positieve invloed hebben op het adaptatiegedrag. Geldoverdrachten voor aanvang van de droogte, relevante training voor agrariërs, nauwkeurige vroegtijdige waarschuwing en toegang tot kredietmarkten zorgen ervoor dat boeren gemiddeld respectievelijk +11%, +51%, +54% en +7% vaker een maatregel gaan nemen.

**Het ADOPT model**

Op basis van de bovenstaande informatie, heb ik een innovatief droogterisicomodel, ADOPT, gecreeërd. ADOPT richt zich op adaptatiebeslissingen (irrigatie, landbeheer) door individuele agrariërs en hun interactie met droogtegevaar, blootstelling en kwetsbaarheid. ADOPT integreert een model voor de productie van water voor gewassen met een model over het maken van beslissingen over adaptatie-maatregelen. Ik berekende dat het maken van Fanya Juu-terrassen, het toedienen van mulch, het bouwen van ondiepe waterputten en gebruiken van drip irrigatie systemen het effect van droogte op landbouwproductie kan verminderen.

Daarnaast simuleert ADOPT het heterogene adaptief gedrag van agrariërs in Kenia op een endogene manier. Hierbij wordt de wederzijdse interactie tussen enerzijds hun adaptatie-beslissingen en anderzijds hun land en productie, die worden blootgesteld aan droogte, expliciet gemaakt. Een bestaande psychologische theorie (de Protection Motivation theory) wordt vergeleken met scenario's van economische rationaliteit en van geen adaptatiebeslissingen, om verschillende gedragsaannames te testen. Ik laat zien dat ADOPT, door ervan uit te gaan dat boeren begrensd rationeel adaptief gedrag vertonen, in staat is om de evolutie van adaptatiebeslissingen en historische opbrengsten na te bootsen. ADOPT kan zo nauwkeurigere schattingen van de impact van droogte op toekomstige voedselzekerheid bereiken.




### Toepassing van het ADOPT model

Ten slotte heb ik ADOPT aangepast om te kunnen simuleren hoe kleine agrariërs in Kenia reageren op interventies van het droogtebeleid door de overheid en (toekomstige) mogelijke klimaatverandering. Hierbij werden de drijfveren en belemmeringen voor implementatie en de sociale interacties tussen agrariërs wederom expliciet meegenomen. Geldoverdrachten voor aanvang van de droogte, relevante training voor agrariërs, nauwkeurige vroegtijdige waarschuwing en toegang tot kredietmarkten kunnen kleine agrariërs helpen om zich voor te bereiden op naderende droogte en zo onnodige schade vermijden. Het model bevestigde dat elk van deze beleidsacties een positief effect heeft op de adaptatiebeslissingen van kleine boeren.

Ik ontdekte dat het combineren van alle vier de beleidsacties, en dus het aanpakken van meerdere belemmeringen voor aanpassing tegelijk, resulteert in niet-lineaire positieve effecten op de kwetsbaarheid van kleine boeren (tussen -5% en -70% huishoudens met voedseltekorten). Een dergelijke holistische, prospectieve kijk op het verminderen van droogterisico's bleek de enige te zijn die robuust was onder alle verschillende klimaatveranderingsscenario's. Het zorgt voor een vermindering van de hulpbehoeften van minstens -68%, zelfs in een heter en warmer toekomstig klimaat. Deze proof-of-concept-toepassing van ADOPT toont aan dat het effect van proactieve beleidsacties kan worden geëvalueerd aan de hand van een dynamisch droogterisicomodel. Ik verwees ook naar het vertraagde effect van beleid zichtbaar in de resultaten van ADOPT: beleidsmakers zouden nu actie moeten ondernemen om toekomstige effecten op de kwetsbaarheid van kleine boeren in een steeds meer droogtegevoelige wereld te maximaliseren.

**Conclusie**

Het gepresenteerde raamwerk en model zijn zeker geen ultieme oplossing op zich. Het is voornamelijk bedoeld om aan te tonen hoe een interdisciplinaire onderzoek het droogterisico beter kan modelleren; en voor het initiëren van discussies over de gegevensvereisten en resterende onderzoeksvragen. Dit proefschrift geeft echter ook een praktisch voorbeeld van hoe we ons begrip van mogelijke evoluties van droogterisico onder klimaatverandering en risicoverminderings-strategieën kunnen verbeteren. Daarnaast demonstreert het gebruik van risicomodellen die adaptief gedrag integreren als beslissingsondersteunend instrument om prioriteit te geven aan effectieve adaptatiestrategieën in een steeds meer droogtegevoelige wereld.

# SUMMARY

*Drought disaster risk models have long neglected the potential of people and communities to adapt to the serious hazard posed by droughts. Failing to account for the dynamic nature of individual human adaptive behaviour leads to incomplete risk estimates.* Therefore, this thesis explored how to *integrate heterogeneous individual adaptive behaviour in drought disaster risk assessments*. It acknowledges the unique characteristics of droughts and details how to deal with adaptation decisions and their interaction with drought disaster risk. This thesis proposes a conceptual framework to guide modellers to address the dynamic nature of drought disaster risk in time and space. The framework suggests the use of agent-based modelling (ABM) approaches to capture the socio-hydrologic feedback between individual and collective human adaptation decisions and drought hazard, exposure, vulnerability, and impacts. The framework allows for assessing how the adaptive behaviour of different stakeholders might influence drought disaster risk over time and space. This framework provides a test-bed for understanding and modelling drought disaster risk dynamics.

Multiple data collection activities were conducted to disentangle the *complexities of drought adaptive behaviour*. Considering the factors in prevailing behavioural theories (e.g., expected utility theory for rational decision making; protection motivation theory for bounded rational decision making), different drivers and barriers for the adoption of adaptation measures among smallholder farmers in Kitui, Kenya were analysed using survey information. The results indicate that mistrust in forecasting (-29%) and a strong belief in God (-58%) serve as barriers to adaptation, while participating in farm groups (+38%) and past adaptation decisions (+44%) stimulate the intention to adopt new drought adaptation measures. This research therefore confirms the importance of several components of existing bounded rational behavioural theories; however, none of the evaluated behavioural theories alone could fully explain the observed behaviour. Moreover, the results indicate that new policy actions would support smallholder farmers to adopt drought adaptation measures. Potential policy actions include *ex-ante* cash transfers, timely extension services, tailored early-warning systems, and access to credit markets. These policies would increase the adaptation intention by +11%, +51%, +54%, and +7% (per percentage reduced interest rate), respectively.

A novel drought disaster risk adaptation model, ADOPT, was developed based on this empirical information. ADOPT combines a crop-water model with an agent-based decision model and *simulates small-scale agricultural adaptation decisions in response to drought disaster risk*. The assumptions on adaptive behaviour were tested through the application of various behavioural theories. The results demonstrate that, by accounting for bounded rational adaptation behaviour (following protection motivation theory), ADOPT is better able to reflect historic crop yield dynamics, food security, and poverty levels compared to simulations using rational decision making under expected utility theory. Moreover, including individual household characteristics leads to a better representation of the processes leading to food-aid needs. Thus, estimations of drought disaster risk can be improved using a socio-hydrologic, agent-based approach.

ADOPT was also used to simulate how smallholder farmers respond to pro- and reactive drought policy interventions and (future) drought events. The results confirm that *education, financial aid, and awareness can reduce smallholder farmers' vulnerability to drought under climate change*. Combining *ex-ante* cash transfers (financing early action rather than recovery), tailored extension services (seasonal on-farm trainings), timely early-warning systems (local drought monitoring and prediction), and access to credit markets (affordable micro-finance options) results in non-linear positive effects on smallholder drought vulnerability (between -5% and -70% households in food shortage compared to the situation without implementation of these policies). Adopting this holistic, prospective view on drought disaster risk reduction, and thus simultaneously targeting multiple barriers to adaptation, proved robust under all different climate change scenarios and reduced aid needs by -68% under a hotter and drier future climate. This proof-of-concept application of ADOPT also demonstrates the delayed effect of policies by one to two decades, urging policy makers to act now in order to maximise the future effects on drought vulnerability in an increasingly drought-prone world.

*This research contributes to drought disaster risk science through exploring the potential of explicitly including the adaptation decisions of smallholder farmers in agricultural drought disaster risk assessments.* The presented conceptual framework and the ADOPT model are by no means an ultimate and exclusive solution but are mainly intended to demonstrate how drought disaster risk dynamics should be modelled with an interdisciplinary approach. This thesis demonstrates a practical example of how to improve understanding of possible evolutions of drought disaster risk under climate change and risk reduction policies. In addition, it showcases ways to support the heterogeneous smallholder farmers in Kenya's drylands to adopt effective adaptation measures in order to achieve the Sustainable Development Goals 'no poverty' and 'zero hunger'.

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# CHAPTER 1:

## DROUGHT DISASTER RISK AND HUMAN ADAPTIVE BEHAVIOUR

## *AN INTRODUCTION TO THIS THESIS*

***"How can we support societies to adapt to changing conditions by considering the uncertainties and feedbacks between natural and human-induced hydrological changes?"***

- *Panta Rhei science question* 6 (Montanari et al. 2013)

# 1. Solving the 'water question': The current status of drought disaster risk research

## 1.1. Drought disaster risk in context

'Drought is on the verge of becoming the next pandemic and there is no vaccine to cure it,' declared Mrs. Mami Mizutori, the UN Secretary-General's Special Representative on Disaster Risk Reduction, at the launch of the Special Report on Drought 2021 (UNDRR news, 2021). Droughts often cause economic decline in the affected region, perpetuating existing under-development and increasing social inequalities (Cammalleri et al., 2021; Herrero et al., 2010). Concerns about the influence of climate change on droughts and the rising number of drought disasters (CRED, 2017, 2019) have made droughts a timely topic of interest. This rising interest has prompted broad calls for action to governments and institutions, such as the UNCCD Global Drought Initiative and the 2018-2028 UN action decade on water, and requests to the scientific community for innovative advice on how to deal with drought disaster risk (Nature editorial, 2019, 2021).

Droughts, defined as prolonged periods of exceptional lack of water compared to normal conditions, are recurring features of the climate and should not be confused with the interrelated phenomena of aridity and water scarcity (Van Loon, Gleeson, et al., 2016). They are disruptive hazards that affect large areas and a disproportionate number of people (Carrão et al., 2017). Droughts can trigger direct and indirect and short- and long-term harmful effects on society and the environment, and drought impacts can cascade through the socio-economic system. For example, water deficits caused by drought events can lead to reduced food production. This effect, in turn, can lead to loss of livelihoods, resulting in increased poverty levels, as well as food availability issues and thereby increased food prices (CRED & UNDRR, 2020).

In semi-arid, agriculture-dependent regions, droughts often lead to malnutrition, famine, and the need for food aid, with the most vulnerable hit the hardest (d'Alessandro et al., 2015; Below et al., 2007). The increasing frequency and severity of droughts, combined with a context of chronic vulnerability and inequality, is placing growing pressure on the livelihoods of many smallholder farmers in these regions (Government of Kenya, 2018; Kuhn et al., 2016; Republic of Kenya, 2015). As global food production relies heavily on smallholder rain-fed agriculture (<3ha), reducing the climate vulnerability of smallholder farmers is critical to achieving the SDGs (FAO, IFAD, UN Decade of Family Farming 2019-2028; Marenya & Barrett, 2007; Mutuku et al., 2016). However, despite the disproportionate adverse effects of droughts on smallholder farmers, the majority of the research on the impact of climate change on agriculture has been conducted in industrialised countries (Claessens et al., 2012; van Valkengoed & Steg, 2019). As a result, there is a knowledge gap regarding the vulnerability of small-scale farmers to drought, particularly with regard to effective adaptation strategies that can reduce vulnerability and improve resilience (Lottering et al., 2020).

### 1.2. Drought disaster risk reduction

'Curing' droughts (i.e., preventing meteorological droughts from occurring) might be nearly impossible, but drought disaster risk can be mitigated or prepared for in order to reduce droughts' harmful consequences. Adaptation measures can prevent meteorological droughts from propagating through the hydrological cycle and thus from causing disruptions to agriculture and society (Sivakumar et al., 2014; Solh & Van Ginkel, 2014). For example, buffering water in the landscape by retaining rainwater (e.g., rooftop water harvesting, farm ponds), recharging groundwater (e.g., earth trenches, terraces), and reusing water (e.g., drip irrigation; mulching) and other water-efficient climate-smart agricultural practices can play a particularly important role in reducing drought disaster risk in the rural areas of the world (Acacia water, 2020; Acacia Water et al., 2018; Metameta & Kenya Wash Alliance, 2012). Over time, smallholder farmers have adopted field-scale adaptation measures to enhance sustainable agricultural production and decrease agricultural water deficiencies, and more measures to reduce the impacts of future droughts are expected to be implemented (Rockström et al., 2002; Rockström et al., 2003). However, in many places, smallholder farmers face financial, knowledge, market, social, or other barriers to the widespread adoption of drought adaptation measures (Mutoko, 2014).

Drought disaster risk reduction policies by governments or related actions by NGOs can help smallholder farmers to overcome these barriers and enable them to plan for the necessary adaptation measures, thus minimising drought impacts in advance (Tsegai et al., 2018). However, this effort requires a shift from the current reactive management approaches to proactive policies and actions (Cabot Venton, 2018; FAO, 2019; Wieriks & Vlaanderen, 2015). For example, timely finance prior to a disaster, in conjunction with optimised early warning services (Opiyo et al., 2015), can reduce vulnerability and be more cost-efficient than post-disaster compensation (Guimarães Nobre et al., 2019). Such *ex-ante* cash transfers can prevent households from becoming malnourished and diminish food price volatility (Hill & Porter, 2016). Furthermore, farmer field schools or agricultural extension services (tailored farm trainings provided by government or NGO's) can support farmers in monitoring drought disaster risks (Omollo et al., 2018) and, in conjunction with access to a functional (credit) market (Opiyo et al., 2015), can allow them to trial adaptation options (Aryal et al., 2021; Mfitumukiza et al., 2017; Mundy & Jager, 2006). However, there is a need for enhanced knowledge on the viability and sustainability of specific proactive policies and actions aiming to support the adoption of drought adaptation measures among smallholder farmers (Nature News, Padma, 2019).

### 1.3. Drought disaster risk assessment

Developing sustainable, efficient drought disaster risk reduction strategies requires an understanding of the temporal changes of impacts, their respective causes, and human-water interactions (Di Baldassarre et al., 2019; Vanelli & Kobiyama, 2021; Kreibich et al., 2019). Hence, such strategies, policies, and actions should be based on proper drought disaster risk analysis (Enenkel et al., 2020; Kondrup et al., 2020; UNCCD et al., 2013). However, the complex nature of droughts (their relative-to-normal characterisation, slow onset, and delayed impacts) makes it difficult to analyse drought impacts, and current risk assessments exhibit significant shortcomings (Blauhut, 2020; Eriyagama et al., 2009). Analysing the impacts of drought and drought disaster risk requires studying how societies respond to the (changes in) physical processes causing drought, but an open question remains: 'How do hydrological systems interact with, and feedback to, natural and social systems?' (Lloyd-Hughes, 2014; Mishra & Singh, 2011a; Wilhite et al., 1985; Montanari, 2015). The challenges in demarcating a drought event, combined with the challenge of quantifying drought vulnerability and human feedback (Bachmair et al., 2015, 2017; González Tánago et al., 2016), currently limit proper analysis of (the interactions between) drought disaster risk and drought disaster risk mitigation (Van Loon et al., 2016).

#### *Static view on drought disaster risk*

Drought disaster risk results from the complex interaction of drought hazard, exposure, and vulnerability (Vogt & Barbosa, 2018). Drought disaster risk assessments primarily consider historical hazard, exposure, and vulnerability (Carrao et al., 2016; Meza et al., 2020); dynamic future hazards under static exposure and/or vulnerability (Lange et al., 2020; Pokhrel et al., 2021); or dynamic hazards with dynamic exposure (Gu et al., 2019; Smirnov et al., 2016; Kondrup et al., 2020; Mishra & Singh, 2011b; Tabari et al., 2021). Vulnerability has received the least attention in drought disaster risk assessments to date, as it cannot always be described by quantitative indicators (Gopalakrishnan, 2013; Ward et al., 2020). In today's Anthropocene world, the water cycle is constantly altered by human influence and vulnerability is a dynamic process. In addition to climate change, human reactions and interventions to droughts may help some communities, but may also influence the severity and propagation of droughts elsewhere (Holman et al., 2018). However, these dynamic feedback processes—and the resulting spatial and temporal patterns of hazard, vulnerability, and exposure—are not addressed in current drought disaster risk assessment approaches. In particular, vulnerability estimates are usually static, when a dynamic approach including the changing (lack of) adaptive behaviour of people and communities over time would better describe the complexity of drought vulnerability (Hagenlocher et al., 2019). Drought disaster risk models often overlook the emergence of drought adaptation measures. There is thus a need for improved risk assessment approaches that include and combine such adaptation dynamics with other trends, such as climate change, population growth, and socioeconomic development (Ahmadalipour et al., 2019; Tabari et al., 2021).

### ***Socio-hydrologic view on drought disaster risk***

The aforementioned dynamics among different drought drivers, impacts, and responses are complex and include interactions at multiple spatiotemporal scales (UNDRR, 2021). Understanding interactions such as the so-called 'adaptation effect' and 'levee effect' — referring to the observation that more frequent disasters are often associated with decreasing societal vulnerability, and the observation that risk prevention measures can actually lead to increased vulnerability — can be critical in estimating future disaster risk (Di Baldassarre et al., 2015, 2017, 2018; Gonzales & Ajami, 2017; Kuil et al., 2016). Clearly, there are important feedback between the physical and social processes associated with drought disaster risk, and risk models must be able to capture them (Bierkens et al., 2015).

The field of water resources systems analysis has developed concepts and tools to study the opportunities and effects of water abstraction (Brown et al., 2015; Kasprzyk et al., 2018), and the discipline of socio-hydrology has provided frameworks and models to analyse people and societal processes as integral to the human-water system. Socio-hydrological scenario-based, system dynamics, pattern-oriented, heuristic, or agent-based modelling approaches can be used to explicitly address the coupled water-society system by capturing the long-term dynamics produced by the interactions of physical, social, and technical processes (Srinivasan et al., 2016; Sivapalan et al., 2012; Sivapalan & Bloschl, 2015; Troy et al., 2015). These so-called 'socio-hydrological models' are particularly relevant for understanding the risk of climate extremes such as droughts (Blair & Buytaert, 2015a, 2016b). However, existing socio-hydrological models often represent human behaviour as the rational choices of a homogeneous group (Ertsen et al., 2014; Pande & Ertsen, 2014). Such top-down approaches to modelling the human-water system may overlook fundamental processes and miss the heterogeneous adaptive behaviour of individuals using water (Kelly et al., 2013; Mostert, 2017).

### ***Bottom-up view on drought disaster risk***

The importance of incorporating individual human adaptive behaviour is increasingly recognised. However, the inclusion of human adaptation decisions and their interaction with the natural water system in drought disaster risk models remains a major challenge (Filatova et al., 2013; Schlüter et al., 2017). Although individual adaptation influences drought vulnerability and exposure, few drought disaster risk models consider this dynamic interaction from a bottom-up, individual adaptation perspective. Bottom-up modelling techniques, which require representation of the processes that drive system behaviour, can help to understand the complex heterogeneous and individual human decision-making processes regarding drought adaptation measures and how they affect and are affected by hazard, exposure, and vulnerability (Blöschl & Sivapalan, 2016). Indeed, to fully integrate human processes, a framework that includes human drivers, impacts, feedback, and the changing hydro-meteorological conditions causing drought in the Anthropocene is needed (McMillan et al., 2016).

Aerts et al. (2018) advocated for agent-based models (ABM) to describe the interaction of hydrological and human-adaptive processes. These models represent a bottom-up approach to system modelling, simulating the adaptive actions of individual agents, particularly their way of (re)acting with other agents and the environment (Blair & Buytaert, 2015a). The focus of ABMs is on the behaviour and decision making of individual agents within a system. System dynamics can then be evaluated through assessing the collective effect of individual decisions (Bouziotas & Ertsen, 2017): agents can learn from other agents and/or extreme events, and they are influenced by and can adapt to external drivers such as climate change or top-down interventions. For example, the government may set water price taxes, which influence irrigation decisions by farmers and thereby affect the water resources system. In ABMs, the actions and decision processes of all agents are described by behavioural decision rules. Creating these rules in itself is quite complex (Schlüter, Baeza, Dressler, Frank, Groeneveld, Jager, Janssen, Mcallister, et al., 2017), but even simple rules can generate complex (emergent) behaviour (Walker et al., 2015).

Agent-based models are increasingly used in human behaviour modelling and disaster risk assessment, such as for flooding (Haer et al., 2016; de Ruig 2021). However, in drought disaster risk assessment, the application of ABMs remains limited (Akhbari & Grigg, 2013; Berger et al., 2007; Troy et al., 2015). Kromker et al. (2008) used ABMs to detect communities vulnerable to drought and identify relevant factors for increasing resilience. They found that the main challenge is sufficient data for a representative model. Other studies have focussed on the feedback between farmers' agricultural activities and available water resources using ABMs (e.g., Ghoreishi et al., 2021; Molajou & Afshar, 2021; Pouladi et al., 2020). More research in this direction is required in order to create full-fledged agent-based drought disaster risk models that can support the design and evaluation of proactive drought disaster risk reduction strategies (Kreibich et al., 2020; Schrieks et al., 2021; Ward et al., 2020).

## 2. The need to improve drought disaster risk models by including vulnerability dynamics

Dynamic drought disaster risk models must take into account the effects of adaptive or non-adaptive human behaviour on drought disaster hazard, exposure, and vulnerability (Montanari et al., 2013). To understand such adaptation dynamics, one needs to understand the sensitivities to drought and adaptive capacities of those making decisions on adaptation measures (UNISDR, 2007). Furthermore, a realistic representation of human adaptive behaviour should be included. Human decision rules in existing drought disaster risk models are often presented as the rational behaviour of a homogeneous group. However, in reality, individual adaptation decisions are largely heterogeneous in space and time and bounded in rationality: decisions are heavily influenced by individual perceptions and attitudes, leading to different adaptation patterns (Gebrehiwot & van der Veen, 2015b; Huber et al., 2018; Keshavarz & Karami, 2016; Malawska & Topping, 2016; van Duinen et al., 2015b, 2016a, 2016b). Therefore, drought disaster risk models should focus on the spatial and temporal agency level of individuals (Ertsen et al., 2014). This focus can be achieved by taking humans as the starting point for assessment and concentrating on the local physical and social processes that determine drought disaster risk (Conway et al., 2019a).

Incorporating human adaptive behaviour and the resulting heterogeneous adaptation decisions is challenging (Loucks, 2015; Tesfatsion et al., 2017) and often done based on *ad hoc* assumptions without a solid theoretical and empirical basis (Groeneveld et al., 2017b; Müller et al., 2013; Schulze et al., 2017a; Schwarz et al., 2020). Calibrating behavioural, economic, and psychological theories with empirical data can improve the model rules describing complex decision-making (An & López-Carr, 2012; Filatova et al., 2013a; Muelder & Filatova, 2018; O'Sullivan et al., 2016). Schrieks et al. (2021) highlighted several challenges for the future of agricultural drought disaster risk models and argued that in addition to anchoring modelled adaptive behaviour in established behavioural theories, such theories should be selected at an early stage to ensure the full modelling application of the chosen theory. They further emphasised the importance of using quantitative and qualitative empirical methods (such as field experiments and individual household surveys) to provide micro-level data for model parameterisation and behavioural calibration (McMillan et al 2016; Xu et al., 2018). A more theoretical and empirical foundation of agent-based drought disaster risk models is clearly needed.

### *Goal and research questions*

To address the challenges described above, this thesis **develops a drought disaster risk model able to account for the dynamics in drought vulnerability through explicitly incorporating the two-way feedback between individual adaptation decisions and the agro-hydrological system**.

In order to achieve this goal, this thesis examines the following research questions:

A. *What modelling approaches are suitable for simulating individual adaptive behaviour in drought disaster risk management?*

B. *Which socio-economic, cognitive, and policy factors influence the decision making of smallholder farmers facing droughts?*

C. *How do different assumptions about the adaptive behaviour of smallholder farmers influence agricultural drought disaster risk estimations?*

D. *Which external policy actions targeting smallholder farmers effectively reduce agricultural drought disaster risk under climate change?*

To find answers to these questions and aiming **to improve the understanding of current and future agricultural drought disaster risk under socio-economic, policy, and climate trends**, I developed an agent-based dynamic drought disaster risk model for a case study in Kenya. This model, ADOPT, is able to simulate the effect of policies on smallholder farmers' drought adaptation decisions and resulting drought disaster risk and can evaluate the robustness of these policies under climate change.

### 3. The case of smallholder farmers' drought disaster risk in semi-arid Kenya

Arid or semi-arid regions, where water demand often exceeds the perpetually low water availability, experience the most severe impacts of droughts (Van Loon, 2013). Moreover, the consequences of droughts are most acute in the Global South, where exposure and vulnerability to drought are high (AghaKouchak et al., 2021). Droughts affect African semi-arid regions more than any other continent, with nearly 150 recorded events in the last 20 years (EM-DAT). The rural areas of Africa, inhabited by pastoralists and smallholder farmers, are the most exposed to drought disaster risk (Winsemius et al., 2018). Climate change has already significantly reduced soil moisture and increased surface air temperature on the continent (Sheffield & Wood, 2008), and it is estimated that drought disaster risk will continue to increase (Ahmadalipour et al., 2019; Global Water Partnership Eastern Africa, 2015; WMO, 2019). Children born in in Sub-Saharan Africa in 2021 will experience 6.3 times more droughts under 1.5 °C global warming than without climate change (Thiery et al., 2021). While droughts might be reasonably predictable, slow preparedness and low adaptive capacity still place communities in emergency situations (Funk & Shukla, 2020).

This thesis focusses on the semi-arid areas in Kenya in specific because drought has been the most catastrophic threat in Kenya for decades (Republic of Kenya, 2014), with a total of 57 million people affected since 1970 (EM-DAT, 2021). Droughts account for 15% of recorded disasters in Kenya, but 82% of people affected by disasters in the past two decades (Gebrechorkos et al., 2019). Consecutive years of drought (e.g., 2012-2016) or extreme drought events (e.g., 2019) lead to an increased risk of famine (Government of Kenya, 2011). Since 2014, Kenya has been almost constantly affected by drought emergencies (Reliefweb, 2021), with the government of Kenya declaring a national drought emergency as recently as September 2021 (Kenya Food Security Steering Group, 2019; FEWSNET, 2018; OCHA, 2017; OXFAM, 2017; The Guardian, 2021; UNICEF, 2019). The effects of climate change are already being experienced by communities living in Kenya's drylands, and water scarcity poses the main constraint to sustainable socio-economic development (Mwangombe et al., 2011).

As agriculture is vital to Kenya's economic growth, this thesis zooms in on three rural districts in the southeast of Kenya's mixed marginal agriculture zone. In Kitui, Machakos, and Makueni, smallholder farming is practised by 91% of the population (FEWSNET 2010). Together with the West Lake region, this is the largest rainfed growing area for maize, the staple crop in Kenya. However, it is also one of the five geographical clusters in Kenya's arid-semi-arid lands that are particularly drought prone (Republic of Kenya, 2013) and it is expected to see an increased drought hazard under climate change (Figure 1.1 and 1.2). Droughts, in addition to the high sensitivity of maize to moisture stress (D'alessandro et al., 2015; Mbogo et al. 2013) and the low level of adopted drought adaptation measures (Lasage & Verburg, 2015), result in a very high variability in yields in these districts (Oluoko-Odingo, 2011; Omoyo et al., 2015; Rao et al., 2011). Failed harvests quickly lead to food insecurity (Johnson & Wambile, 2011; Njoka et al. 2016); therefore, increasing the crop productivity and climate resilience of smallholder farming systems is critical to achieving the development agenda of Kenya Vision 2030 (Government of Kenya, 2012; Hill et al., 2014) and the Sendai Framework's goal of reducing disaster risk (Aitsi-Selmi et al., 2015; Nobre, 2018) (CIAT & World Bank, 2015).

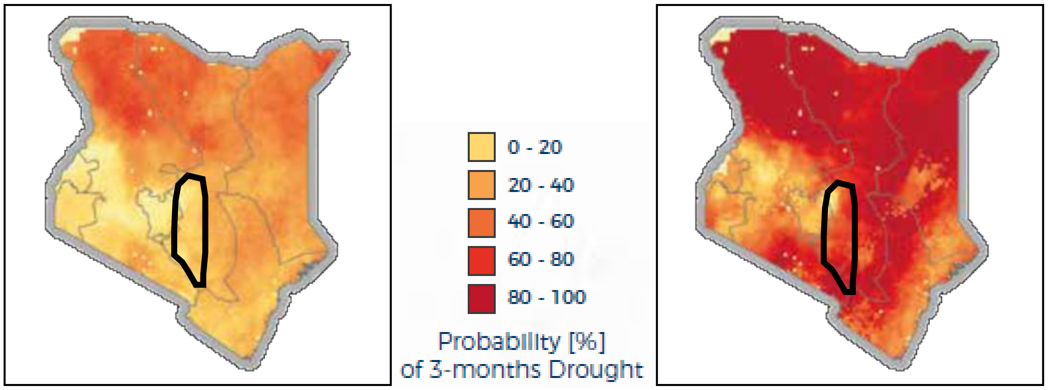


*Figure 1.1: Average annual chance of a meteorological drought occurring (%) under current (1980-2016; left map) and future (2050-2100 under RCP 8.5; right map) climate conditions (Rudari et al. 2019). Study area demarcated in black.*

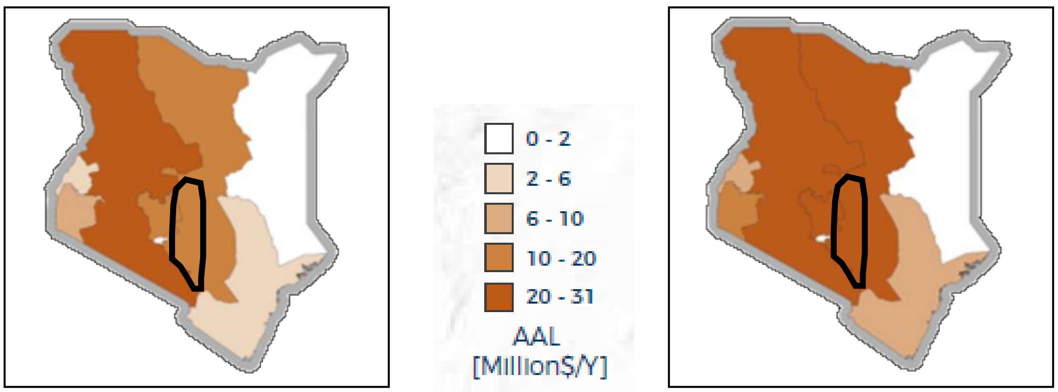


*Figure 1.2: Direct agricultural loss in Kenya (left: risk under present climate; right: risk under projected climate using RCP8.5), in average annual million dollars (Rudari et al. 2019) . Study area demarcated in black.*

## 4. Reading guide

In the following Chapters of this thesis, I detail the framework, design, development, and application of a drought disaster risk model (Figure 1.3).

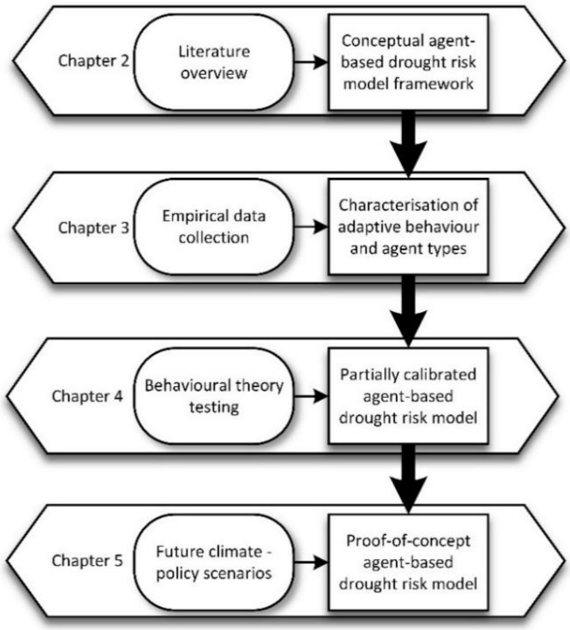


*Figure 1.3: Overview of PhD thesis*

In Chapter 2, I describe the conceptual modelling framework. This modelling framework demonstrates how to build dynamic drought disaster risk models that include human adaptive behaviour. I elaborate the pertinent feedback loops between people and their natural and social environment and discuss relevant theories related to individual adaptive behaviour under risk.

In Chapter 3, I identify and quantify the factors that influence the adaptive behaviour of smallholder farmers facing drought disaster risk through analysing interviews with key informants and the results of a semi-structured household questionnaire. I explain how the resulting information can be used to tailor the decision rules in an ABM.

In Chapter 4, I develop the dynamic drought disaster risk model using the concepts from Chapter 2 and the survey results from Chapter 3. The resulting model, ADOPT, simulates the two-way feedback between adaptive water management by smallholder farmers and changing hydrological conditions by combining behavioural theories with the crop-water model AquacropOS.

In Chapter 5, I present an application of the dynamic drought disaster risk model ADOPT. I demonstrate how the model can be used to estimate the changes in drought disaster risk under six climate change scenarios and four disaster risk reduction policies. I evaluate the effectiveness and robustness of such top-down actions on the reduction of food insecurity, poverty, and emergency aid need.

Chapter 6 contains the synthesis of this thesis. In this final Chapter, I answer the research questions posed in this thesis. I highlight the innovations of the ADOPT model and discuss some limitations to the current model design. I conclude with an overview of the implications of this research for science and society.

## GLOSSARY

Glossary based on terminologies used by the United Nations Office for Disaster Risk Reduction, United Nations Convention to Combat Desertification, or the Integrated Drought Management Programme.

| | |
|---|---|
| **Adaptation** | The adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects. |
| **Adaptive capacity** | The ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences. |
| **Adaptation credit market** | Agricultural micro-credit market with low-interest rates for micro-finance regarding climate adaptation measures |
| **Aridity** | Characteristic of a climate relating to insufficiency or inadequacy of precipitation to maintain vegetation. Aridity is measured by comparing long-term average water supply (precipitation) to long-term average water demand (evaporation). If demand is greater than supply, on average, then the climate is arid. |
| **Disaster risk reduction** | Disaster risk reduction is aimed at preventing new and reducing existing disaster risk and managing residual risk, all of which contribute to strengthening resilience and therefore to the achievement of sustainable development. |
| **Drip irrigation** | Drip irrigation is an irrigation method designed for minimum use of water and labour for the optimum irrigation of plants in arid and semi-arid regions. It allows the slow and precise delivery of water to crops. (WOCAT SLM Database) |
| **Drought (event)** | Prolonged period of abnormally dry weather sufficiently caused by the lack of precipitation or elevated temperature, causing a serious hydrological imbalance. The manifestation of a drought hazard at a particular place during a particular period. |
| **Drought impact** | A specific - positive or negative, primary or secondary - effect of drought on the economy, society, and/or environment, which is a manifestation of risk. |
| **Drought disaster** | A serious disruption of the functioning of a community or a society at any scale due to drought events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts. The effect may test or exceed the capacity of a community or society to cope using its own resources. |
| **Drought disaster risk** | The potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific period, determined |

| | |
|---|---|
| | probabilistically as a function of drought hazard, exposure, vulnerability and coping capacity. |
| **Drought hazard** | The collective of prolonged deficiencies in hydro-meteorological variables that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation. |
| **Drought exposure** | The people, infrastructure, housing, production capacities and other tangible human assets located in drought-prone areas. |
| **Drought vulnerability** | The conditions determined by physical, social, economic and environmental factors or processes which increase the sensitivity of an individual, a community, assets or systems to drought hazard. The degree to which a system is susceptible to, or unable to cope with, adverse effects of droughts. |
| **Early warning system** | The set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities, and organizations threatened by a hazard to prepare to act promptly and appropriately to reduce the possibility of harm or loss. |
| **Ex-ante cash transfer** | Anticipatory cash transfers based on the national early warning system. Cash assistance paid out before the disaster manifests, based on impact predictions of said disaster event (WFP) |
| **Extension services** | An agricultural extension service offers technical advice on agriculture to farmers and supplies them with the necessary inputs and services to support their agricultural production. It provides information to farmers and passes to the farmers new ideas developed by agricultural research stations. (FAO) |
| **Fanya Juu terrace** | Terrace bund in association with a ditch, along the contour or on a gentle lateral gradient. Soil is thrown on the upper side of the ditch to form the bund, which is often stabilized by planting a fodder grass. (WOCAT SLM Database) |
| **Mulching** | Covering the soil with mulch protects it against wind and water erosion and provides nutrients, which has a positive effect on yields and food security. (WOCAT SLM Database) |
| **Shallow well** | Groundwater well of limited depth and size, often build by individual farmers. It is used to pump groundwater to provide water for irrigation while controlling the groundwater table in recharge areas. (WOCAT SLM Database) |
| **Water scarcity** | An imbalance between supply and demand of freshwater in a specified domain (country, region, catchment, river basin, etc.) as a result of a high rate of demand compared with available supply, under prevailing institutional arrangements (including price) and infrastructural conditions. |

# CHAPTER 2:

# INTEGRATING HUMAN BEHAVIOUR DYNAMICS INTO DROUGHT DISASTER RISK ASSESSMENTS

## *A SOCIO-HYDROLOGIC, AGENT-BASED APPROACH*

*This Chapter is published as:*

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**Samenvatting**

Droogte vertegenwoordigd een hardnekkig en kostelijk gevaar dat gevolgen heeft voor mens en milieu. Naarmate de klimaatvariabiliteit blijft toenemen en verdere sociaaleconomische ontwikkeling de verdeling van rijkdom en mensen beïnvloedt, zal het droogterisico in vele delen van de wereld toenemen. De unieke kenmerken van droogte - namelijk haar trage begin, haar grote ruimtelijke en temporele omvang, haar door-de-mens-beïnvloede verspreiding, en haar gevolgen die slechts vertraagd en ook op verschillende plaatsen waargenomen worden - maken het moeilijk om de impact ervan correct in te schatten. Een verdere complicatie bij deze berekening is het vermogen van de mens om vóór, tijdens en na een droogtegebeurtenis maatregelen te nemen, wat op zijn beurt de verwachte impact wijzigt. In die zin is droogte zowel een sociale als een hydro-klimatologische kwestie. Risicoperceptie is een van de belangrijkste factoren bij het nemen van aanpassingsbeslissingen, maar de meeste modellen houden geen rekening met de wijze waarop mensen risico's zien en erop reageren, en met name met de wijze waarop ervaringen door de tijd heen van invloed zijn op beslissingen.

In dit hoofdstuk beschrijven we een raamwerk dat de traditionele benadering van risicomodellering uitbreidt en vervolledigd met de feedback tussen de beslissingen over droogtemaatregelen en blootstelling aan droogte, kwetsbaarheid en gevaar. We bespreken hoe een sociohydrologische, agent-gebaseerde modelopzet het menselijke aanpassingsgedrag met betrekking tot droogtemaatregelen kan simuleren, en hoe dit kan helpen om te onderzoeken hoe het nemen van droogtemaatregelen het voorspelde droogterisico kunnen beïnvloeden. We suggereren dat een dergelijke aanpak vooruitgang kan brengen in begrijpen van adaptief gedrag in een wereld die in toenemende mate droogtegevoelig wordt. De voorgestelde aanpak kan leiden tot een betere prioritering van strategieën voor aanpassing aan droogte; en tot een verfijnde voorspelling van toekomstige scenario's.

## Summary

Droughts are a persistent and costly hazard impacting human and environmental systems. As climate variability continues to increase and socio-economic development influences the distribution of wealth and people, drought disaster risk is expected to increase in many parts of the world. The unique characteristics of droughts - namely their slow onset, large spatiotemporal extent, human-influenced propagation, delayed impacts and teleconnection potential – make it difficult to correctly assess drought impact and calculate risk. Further complicating this calculation is the capacity for humans to make adaptive decisions before, during, and after a drought event, which in turn alters expected impacts. In this sense, droughts are equally a social and hydro-climatic issue. Risk perception is one of the main factors driving adaptation decisions, yet most models neglect how humans respond to risk, and in particular how experiences influence decisions through time.

In this Chapter, we describe a framework that extends the traditional risk modelling approach to include the two-way feedback between the transient adaptation decisions and drought exposure, vulnerability and hazard. We discuss how a socio-hydrologic, agent-based modelling setup, focused on individual and collective actions, can simulate the adaptive behaviours of different stakeholders to examine how emergent actions might influence projected drought disaster risk. We suggest such an approach can provide a testbed for understanding adaptive behaviours in an increasingly drought-prone world and could allow for better prioritization of drought adaptation strategies; refined understanding of future scenarios; and a vehicle to drive planning and resilience building

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## 1. Introduction

Droughts are defined as unusual and temporary deficits in water supply and can result in wide-ranging economic, social and environmental impacts (IPCC, 2007; Wilhite, 2000). At a global scale, droughts affect nearly 75 million people annually (CRED & UNISDR, 2018) and increasing climate variability, population growth, and economic development have contributed to increasing global drought impacts (Alcamo, Flörke, & Märker, 2007). These trends can be expected to continue, further intensifying drought disaster risk conditions (IPCC, 2012; Kummu et al., 2016; Taylor et al., 2010; Vörösmarty et al., 2010; Hyndman, 2014). Besides, since droughts provoke competition over water resources, building resilience is inherently a multi-criteria problem (Kanta & Berglund, 2015). Droughts pose a particular threat to regional and global food security where losses have the potential to ignite – or contribute to -- political instability, trade issues, mass migration and conflict (Dermody et al., 2017; Kelley et al., 2015; Rüttinger et al., 2005). In a more connected and less certain world, identifying strategies for minimizing drought disaster risk poses one of the greatest challenges of the 21st century (Gain, Giupponi, & Wada, 2016; Sadoff et al., 2015).

Multiple hydrological models have been developed to address uncertainties in water availability. Many stem from the global water crises of the late 1980s and focus on integrating simulations of supply and demand at regional scales (Bierkens et al., 2015). While many studies have identified methods for defining, predicting, and modelling physical drought occurrence, their treatment of human interactions have either been non-existent, or overlaid on a static snapshot of historic norms (Mishra & Singh, 2010, 2011; Van Loon et al., 2015, 2016; Wada et al., 2017). Accurately estimating and communicating future drought disaster risk requires an understanding of the internal and external changes to the hydrologic system (Elshafei et al., 2014, 2016). These changes are not only climate driven but manifest in changes in human influence on the hydrological cycle and changes to human exposure and vulnerability driven by socio-economic, demographic, policy and water use choices (Folke et al., 2002; Pokhrel et al., 2016; Wanders & Wada, 2015).

Despite considerable advances in understanding how stakeholders innovate and adapt, incorporating these decision-processes within hydrological models has remained a challenge (Groeneveld et al., 2017; Schlüter et al., 2017; Schwarz & Ernst, 2009). Limited studies have worked to include the uncertainty in human behaviour and policies and even fewer have explored how transient adaptation strategies might alter water availability scenarios (e.g., Barthel et al., 2008; Bouziotas & Ertsen, 2017; van Duinen, Filatova, & van der Veen, 2012). This suggests there is a major gap in the way we forecast, plan for, and model drought disaster risk (Blair & Buytaert, 2016).

In this light, this Chapter aims to: (1) discuss why traditional disaster risk models are inadequate for addressing the dynamic nature of drought disaster risk, (2) highlight how socio-hydrologic and agent-based modelling approaches can offer improvements and (3) provide a framework that integrates adaptive behaviour and the traditional disaster risk equation.

***BOX 1** drought disaster management: water flows as one dictates*

The need for disaster response (e.g., relief aid, or temporary migration) and recovery (e.g., re-building infrastructure and installing new capacity) occurs both during and after an event. Reactive actions are often costly and can exceed economic capacity (Logar & van den Bergh, 2013; González et al., 2016; Ifejika, 2010). A generally less costly option is proactive adaptation action, i.e., adjustment in the natural or anthropogenic systems in response to expected climatic stimuli or their effects. Such measures aim to prevent new risk (e.g., through sustainable water management), mitigate existing risk (e.g., through rainwater retention), or prepare communities to live with residual risk (e.g., through water-efficient economic activities). Adaptation measures can be initiated in a top-down or bottom-up way–and can be implemented at a range of scales (UNISDR, 2009b, 2009a, 2012).

A common way to categorize adaptation measures is differentiating between structural and non-structural measures (UNISDR, 2015a). In the case of drought, structural adaptation measures, such as the construction of reservoirs, can reduce disaster risk by targeting the hazard and its propagation through space and time (Wagener et al., 2010; Jenkins, 2011). Such measures can create trade-offs that minimize short-term or local impacts at the expense of long-term or downstream water supply. Further, they are generally less able to flexibly accommodate changes in supply and demand. In contrast, non-structural measures reduce drought impact through policies, public awareness, training and education (Elagib, Musa, & Sulieman, 2017; Fuchs et al., 2017; Wutich et al., 2014). These adaptation measures, (e.g., market, regulatory or nature-based solutions) aim to influence drought disaster risk by changing the exposure and vulnerability of local communities and assets (Khatri-Chhetri et al., 2017; Sadoff et al., 2015). The collection of structural and non-structural adaptation measures describes a community's capacity to cope with droughts. By preventing the hazard, mitigating its impact and preparing to live with the residual harmful consequences, humans can alter the drought disaster risk in multiple ways.

## 2. Components of a traditional drought disaster risk model

Drought disaster risk reflects the interaction between hydro-climatic systems, and the vulnerability of exposed people, economies and ecosystems (Beckage et al., 2018; Sayers et al., 2015). It is a measure of the potential impact resulting from the magnitude of a drought and is calculated as the conditional expectancy of experiencing harmful consequences over a certain time period (UNISDR, 2015b): Risk = Hazard x Exposure x Vulnerability. Adaptation measures (box 1) are often included in risk estimations and serve to decrease vulnerability (Lasage et al., 2014, 2015). That said, such measures can also alter exposure and hazard (Lavell et al., 2012). In the following sections, these three risk determinants are discussed with attention to the unique characteristics of droughts and drought adaptation.

### 2.1. Drought hazard

The term natural hazard refers to any "process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation" (UNISDR, 2016). Droughts are hazards stemming from deficits in water supply compared to the long-term mean for a prolonged period (Dracup, Lee, & Paulson, 1980; Van Loon, 2015). Such deficits can be precipitation driven (atmosphere), stream flow driven (surface), soil moisture or groundwater driven (subsurface) deficiencies. While they usually start as precipitation shortfalls, they may or may not, propagate into streamflow, soil moisture, or groundwater droughts through time (Van Loon et al., 2016).

Hazards become disasters when they cause a serious disruption of a society, leading to significant human, material, economic and environmental losses (UNISDR, 2016). While events such as floods and earthquakes make it easy to determine the transition from hazard to disaster, the slow onset, large spatiotemporal extent, human-influenced propagation, delayed impacts and teleconnection of drought events make determining this transition much more challenging. While climate has a large influence on the frequency and intensity of a hazard, human actions (e.g., rainwater harvesting or withdrawals from external sources) can significantly alter the severity of in situ and ex situ water deficiencies and drought propagation through space and time (box 1) (Huang et al., 2017; Van Loon et al., 2012; Vogel et al., 2015; Wang et al., 2016; Weiskel et al., 2007). This phenomenon has been described as human-induced or anthropogenic drought (Alcamo et al., 2007; AghaKouchak et al., 2015; Van Loon et al., 2015; Mehran et al., 2017).

The relationship between the human and physical phenomenon cut across scales, systems and geographies (Polhill, Filatova, Schlüter, & Voinov, 2016), making drought hazard a dynamic, time-dependent outcome of coupled human-water systems (Arneth et al., 2014; Van Loon et al., 2016; Weiskel et al., 2007). As such, a traditional risk approach cannot capture the quintessential drivers of drought hazard. With this recognition, the inclusion of such drivers has been advocated for in the field of water resources system analysis (Brown et al., 2015) and more recently socio-hydrology (Sivapalan, Savenije, & Blöschl, 2012; Troy, Konar, Srinivasan, & Thompson, 2015) but in most cases human actions are represented as collective behaviours predicated on either historic records or stationary projections.

### 2.2. Drought Exposure

Exposure describes the assets and activities located in hazard-prone areas (Birkmann et al., 2013; UNISDR, 2009) and can be expressed as the number of people potentially impacted by water shortages (human exposure) (Kummu et al., 2016); the productive area prone to crop stress (agricultural exposure) (Murthy, Laxman, Sai, & Diwakar, 2014); or the ecosystems that could be harmed (environmental exposure) (Jalava et al., 2014). Due to droughts' large spatial extent, the exposure for a single event can be quite broad and time varying (CRED & UNISDR, 2018). This fact exponentiates when considering droughts can expose assets outside of a hazard's explicit boundary to water deficiencies and economic strains. This teleconnection effect can be illustrated by an example of a meteorological drought in Colorado resulting in downstream surface water deficiencies in California, Arizona, and Mexico or when upstream human decisions significantly alter downstream water availability inducing a non-hydro-climatic drought event (Veldkamp et al., 2017; Ashraf et al., 2017; Odongo et al., 2014; Van Oel, Krol, & Hoekstra, 2012).

In the case of drought, land use is a primary driver of drought exposure and offers a proxy for modelling time-varying exposure. Land use can vary in time and is not disconnected to the occurrence of droughts (e.g., through crop choices or rural-urban migration) (Lobell & Field, 2007). When modelling risk, one cannot ignore how land use changes through the course of a drought event. The effect of drought adaptation measures on land use are only partially included in traditional risk calculations that rely on historic or static land use maps and therefore miss the impacts that individual and community choices have on asset exposure. As such, in addition to representing hazard as a time-varying element of risk, exposure too should be considered as a dynamic driver in risk estimation.

### 2.3. Drought vulnerability

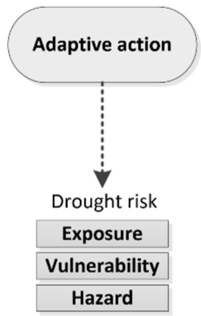
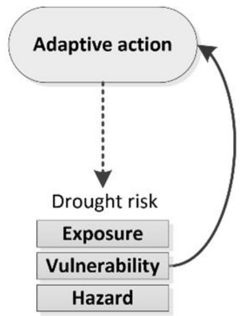
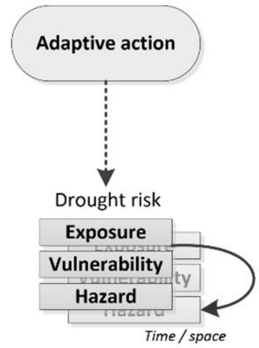
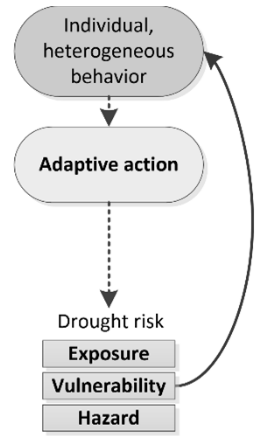
Drought vulnerability formalizes the relationship between drought hazard and its impact on the exposed assets (Blauhut, Stahl, & Kohn, 2015; Urquijo et al., 2014). Vulnerability can be thought of as the combination of a system's sensitivity to risk, and its capacity to cope with the resulting harmful conditions (UNISDR, 2009, Birkmann et al., 2013; Fernandez, Bucaram, & Renteria, 2015). For example, California's semi-arid climate makes the region sensitive to droughts events, increasing its vulnerability. However, the state's infrastructural capacity enables California to cope with water shortage, ultimately decreasing its vulnerability.

Both sensitivity and capacity are subject to human decisions, as they are driven by investments, population growth, adaptation efforts, and historical drought events (Blauhut & Stahl, 2015, 2015b; Carrão et al., 2016). As drought impacts are often delayed, and result from a combination of many dynamic factors, quantifying drought vulnerability is challenging (Eriyagama et al., 2009). Following the trend of hazard and exposure, accessing vulnerability as a static, or even stationary, factor, ignores how its dynamics evolve over time.

***BOX 2** socio-hydrology and drought disaster risk: the reservoir effect*

Socio-hydrology seeks to understand the feedback mechanisms that can emerge from non-linear interactions between different spatiotemporal scales (Blair & Buytaert, 2015). The feedbacks between water supply, demand and drought disaster risk can often result in indirect interactions and counterintuitive dynamics; leading to 'adaptations that can backfire' (Gohari et al., 2013; Kuil et al., 2016). For example, the installation of water harvesting infrastructure has been observed to induce an increase in water use or reduction in water use efficiency. This was witnessed in the Murrumbidgee Basin in Australia, where the construction of dams increased the expansion of irrigation, resulting in abstraction of almost 100% of the natural flows during low-flow periods (Sivapalan et al., 2014) and in the Zayandeh-Rud river basin in Iran, where inter-basin water transfers increased agricultural water demand, triggering severe ecosystem degradation in the donor basin (Ohab-Yazdi & Ahmadi, 2018). Another example was observed in Greece, where population growth and water resource developments were observed to evolve hand in hand: as new water infrastructures favoured network expansions and lower water prices, urban settlements and water-intensive economies expanded (Kallis, 2010). As such, human actions aimed at reducing drought hazard increased exposure and vulnerability due to an over-reliance on the additional water, offsetting the initial benefits of the adaptation measure. This vicious cycle is called the "Peak Water Paradox" (Sivapalan et al 2014) or "Reservoir Effect" (Di Baldassarre et al., 2018). By accounting for the co-evolution of water supply-and-water demand, simulating the feedbacks between adaptation to manage hydrological variability and its effect on risk, socio-hydrologic models may be able to capture counter-intuitive feedback mechanisms that non-interdisciplinary models cannot (Di Baldassarre et al., 2015; Kallis, 2010).

*Table 2.1: Different feedbacks triggered by adaptation choices aimed at reducing drought disaster risk*

| | Baseline influence | Feedback type 1 | Feedback type 2 | Feedback type 3 |
|---|---|---|---|---|
| |  |  |  |  |
| Definition of feedback type | Influence of adaptation on risk (e.g., Sadoff, et al., 2014) | Bi-directional influence between adaptation and risk (e.g., Elshafei, 2016) | Influence of adaptation on risk across spatiotemporal scales (teleconnections) (e.g., Wang et al., 2016) | Influence of risk on individual decision-making behaviour (e.g., Gebrehiwot & van der Veen, 2015) |
| Influence on risk (hazard, vulnerability, exposure) | Adaptation results in a change in one or more of the components of risk, (reducing if effective or increasing if maladaptive) | Adaptation reduces (if effective) or increases risk (if maladaptive). This feedback represents the short-term adjustments in adaptive action due to changing risk | a) Adaptation alters long-term supply of local resources, resulting in future increased or decreased drought disaster risk<br>b) Local implementation may present spill over effects increasing or decreasing drought disaster risk in remote areas | Adaptation may alter decision-making behaviour of individuals (e.g., risk perceptions), resulting in changes in likelihood of undertaking future adaptive action |
| Potential for inclusion in traditional risk equation models | Yes | No | No | No |
| Potential for inclusion in socio-hydrologic models | Yes | Yes | Yes | No |
| Potential for inclusion in socio-hydrologic agent-based models | Yes | Yes | Yes | Yes |

## 3. Including adaptation dynamics in drought disaster risk assessments

So far, we have discussed why static risk calculations cannot accurately depict risk. Acknowledging the two-way interaction between adaptation efforts and drought impact forces us to move away from approaching risk assessment through prescribed, stationary scenarios (Ahmadalipour, 2017; Vogel et al., 2015; Weiskel et al., 2007). In what follows, we highlight some of the human-risk interactions that, we argue, have been under-researched but are critical if one wants to more accurately assess future drought disaster risk. Table 2.1 summarizes examples of different feedbacks triggered by adaptation choices aimed at reducing drought disaster risk and illustrates their potential for inclusion in different modelling approaches. Certainly, other feedbacks can influence risk, such as large-scale weather patterns, but they are beyond human adaptation, hence not the focus here. To include the multi-scalar and temporal feedbacks between the human and physical subsystems, environmental models can be coupled with transient human adaptation models to simulate changes in exposure, vulnerability and drought hazard (Farjad et al., 2017). For example, spatially explicit land use models can replace static land use layers and water resources system models can be used to simulate regional water supply-and-demand dynamics (Weiskel et al., 2007). Socio-hydrologic, agent-based modelling approaches can contribute to the implementation of such multi-models and provide a general framework for conceptualization. As such they are the focus in the remainder of this Chapter.

### 3.1. A socio-hydrologic approach

The relationship between humans and hydrological risk is by no means a simple one (Blair & Buytaert, 2015). Since the 1990s, the fields of hydro sociology (Falkenmark, 1998), water resource system analysis (Zahraie, 2003), the hydro-social cycle (Swyngedouw, 2009), ecohydrosolidarity (Malin Falkenmark, 2009) and socio-hydrology (Sivapalan et al., 2012) have aimed to study people and water through a “system of mutual interaction” (Vogel et al., 2015). Socio-hydrology attempts to address the bi-directional interactions and feedbacks between the human and water systems by treating humans, their activities, and policy decisions as endogenous components of the water system (Sivapalan et al., 2012; Pande & Ertsen, 2014).

Both hydrological and human processes act at different spatial and temporal scales (Blair & Buytaert, 2016). Cross-scale interactions and feedbacks therefore characterize the human-water relationship (Liu, Tian, Hu, & Sivapalan, 2014), and are critical when dealing with the fuzzy borders and slow-onset of drought hazards. By simulating the dynamics and co-evolution of the coupled human-water system, socio-hydrologic models aim to estimate water risk in a more holistic manner (Blair & Buytaert, 2016; Srinivasan, Konar, & Sivapalan, 2017). As such, one can study the evolving use and demand for water in normal, dry and adapted conditions. Examples of these studies are increasingly addressing the inclusion of multiple-users (Noël & Cai, 2017), upstream-downstream and temporal trade-offs (Becu et al., 2003; Van Oel, Krol, & Hoekstra, 2012b), dynamics of conflict / migration (Akhbari & Grigg, 2013), transboundary water management (Khan, Yang, Xie, & Ringler, 2017), virtual water trade (Hoekstra and Hung 2002) and counter-intuitive long-term maladaptive actions, e.g. the reservoir effect (box 2) (Di Baldassarre et al., 2018, 2017; Van

Oel, 2018) within their analyses. These offer a promising baseline for improving risk estimates yet have largely focused on feedbacks 1 and 2 while largely excluding feedback 3 (table 1) (Blair & Buytaert, 2016; Garcia, Portney, & Islam, 2016; Gober et al., 2017; Troy, Pavao-Zuckerman, & Evans, 2015).

While a socio-hydrologic approach has been applied in risk science (Di Baldassarre et al., 2013; 2013b; 2015; Patricia Gober & Wheater, 2015; Khan et al., 2017; Kuil et al., 2016; Van Emmerik et al., 2014), most attempts have focused on the actions of a rational, single-actor group at the expense of interaction between, and bounded-rational behaviour of, individuals, collective water users, and institutions (Bouziotas & Ertsen, 2017; Mostert, 2017; Noël & Cai, 2017). This limitation highlights an opportunity to better study and understand how the emergence of heterogeneous adaptation across space and time can influence risk (Holman et al., 2018). This is particularly relevant for simulating counter-intuitive feedbacks to water consumption influenced by changing risk perceptions (Box 2). An individual actor approach has recently been advocated for in quantifying flood disaster risk (Ciullo et al., 2017; Di Baldassarre et al., 2017; Aerts et al., 2018), however, the unique and different properties of drought make the direct application of the flood methodologies unsuitable and deserving of further discussion.

### 3.2. Accounting for individual bounded-rational behaviour

To include adaptive behaviour in risk assessments, an understanding of how individuals make adaptation decisions in the face of uncertainty is needed (Keshavarz & Karami, 2014). In several socio-hydrologic studies, adaptive behaviour is assumed as proactive, economically rational, objective and effective while assuming perfect risk awareness, adequate early warning systems, and typically excluding socio-economic limitations (other than cost) (Holman et al., 2018; Schlüter et al., 2017).

Figure 2.1 illustrates a conceptual view of dynamic drought disaster risk. In this illustration, drought events are represented by the grey bars. The trend-line labelled 'No Drought Adaptation' indicates an increasing level of risk driven by climate and population drivers. The trend-line labelled 'Rational Adaptation' illustrates the minimum risk level, assuming complete economic - rational adaptation behaviour. However, as most drought adaptation decisions are made reactively, such assumptions are unrealistic (Keshavarz & Karami, 2016; UNCCD, FAO, & WMO, 2013; Wilhite et al., 2014). Empirical studies have shown that observed adaptation decisions cannot always be explained by economic motivations alone but are influenced by personal, bounded rationality (Haer, Botzen, de Moel, et al., 2016; Malawska & Topping, 2016; Patt & Siebenhüner, 2005; van Duinen, Filatova, Jager, & van der Veen, 2016). It is the perception which people have of the hydrological system, rather than its' actual state, which determines the way the system may be managed (Blair & Buytaert, 2016).

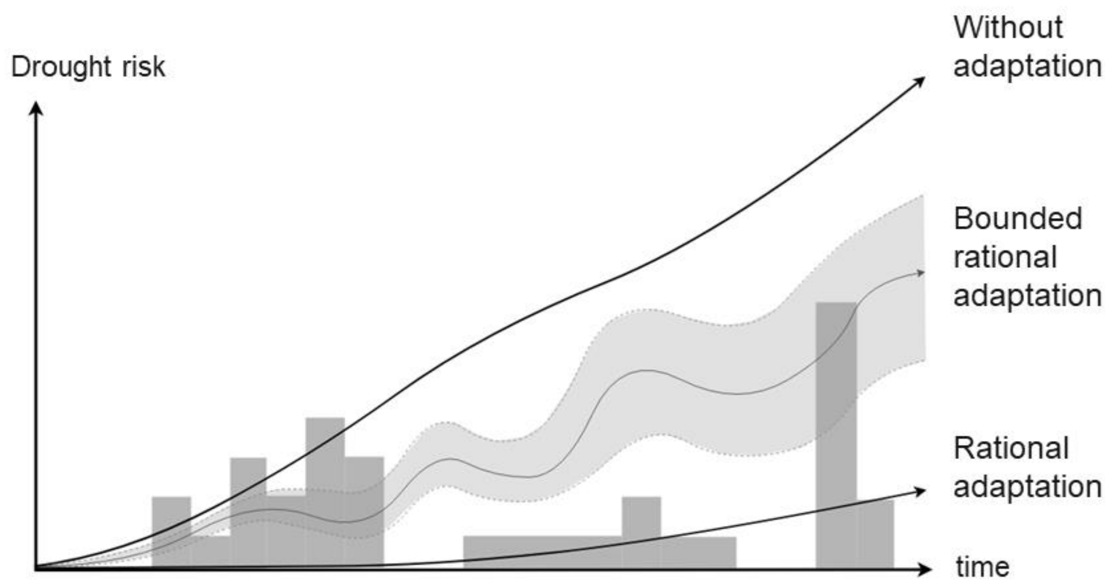



*Figure 2.1: Changing levels of drought disaster risk due to no adaptation (top line), economically rational adaptation (bottom line) and bounded-rational adaptation (shaded area) all influenced by experienced drought events (vertical bars).*

Multiple factors complicate the prediction of bounded - rational adaptive behaviour, such as the perceived adaptation efficiency, the costs of undertaking an adaptive strategy, the (perceived) capacity to enact it (financial or knowledge constraints, technical skills), and risk perception (Bubeck, Botzen, & Aerts, 2012; Grothmann & Patt, 2005; Loucks, 2015). In the context of drought, risk perception relates to how people and institutions perceive both the severity and likelihood of a drought event occurring (Asayehegnet al., 2017; Korte, 2017; Silvestri et al., 2012; Urquijo et al., 2017); it is this flawed perception of reality that leads to the so-called reservoir-effect (Di Baldassarre et al., 2018). Risk perception can be influenced by peoples' memory of past experiences, risk information transferred through social networks, media, or politics, as well as a person's trust in existing forecasting and early warning systems and individual risk-adversity (Loucks, 2015). Thus, the occurrence of drought events influences risk perception, an individuals' risk perception partially defines its adaptive behaviour and resulting adaptation decisions affect future drought disaster risk (Beckage et al., 2018). To illustrate this idea the line labelled 'Bounded Rational adaption' represents the possible evolution of risk driven by transient, bounded-rational adaptive behaviour.

Decision making is both an individual and social process. People differ in the extent they are motivated to protect themselves against drought disaster risk, and have different capacities to do so (Larrick, 1993). Besides, imitation and social learning are subject to network externalities and influence people's adaptation intention and choice of specific measures (Barthel et al., 2008; Kiesling et al., 2013). Often, initial decisions, made by a few, can grow into large collective actions, either through government incentive or social networks (Ertsen et al., 2013; Holman et al., 2018). In this way, the capacity to act on information at the individual level is a significant predictor of adaptation intent (Grothmann & Patt, 2005; CRED & UNISDR, 2018; Haer, Botzen, & Aerts, 2016).

It is crucial to understand the complex adaptive behaviour of agents if we are to include it in drought disaster risk models. This can be achieved by using existing behavioural economic and psychological theories that can be calibrated with empirical methods (An, 2012; Groeneveld et al., 2017; Mueller & Filatova, 2018; O 'sullivan et al., 2016; Schulze et al., 2017). Several behavioural theories of decision-making under risk have already been applied in previous existing coupled human-environment models (Filatova et al., 2013). For example, the Expected Utility Theory (Rabin, 2016; Tieskens et al., 2015) and the Prospect Theory (Kahneman & Tversky, 1979) are the two most prominent theories of decision-making under risk in (behavioural) economics (Groeneveld et al., 2017; Schlüter et al., 2017). Also, the Protection Motivation Theory (Maddux & Rogers, 1983) and the Theory of Planned Behaviour (Ajzen, 1991), two examples of theories based on psychological sciences, are regularly used to model bounded rational adjustment decisions (e.g., Hailegiorgis et al., 2018; Pouladi et al., 2019). There are many other theories, but the above are most common and are explained in a little more detail in box 3a-d. In addition, there are frameworks such as the Consumat framework (Jager et al., 2000), which combine elements from different psychological and economic theories and has been used in several models (Acosta-Michlik & Espaldon, 2008; van Duinen et al., 2016).

***BOX 3a*** *Expected Utility Theory (based on Schrieks, Botzen, Wens, Haer and Aerts, 2021)*

Expected Utility theory (EUT), developed by von Neumann and Morgenstern (1947), is based on the assumption that people are rational decision makers who will always choose the option that gives them the highest expected utility. The theory assumes people have perfect information about the available decision options, the probability of different outcomes and the associated gains and losses (Sen, 2008). In the context of adaptation to drought disaster risks, this would mean that agents have all the necessary information about the available adaptation options and consider the existence of all possible different drought events with different degrees of cost and probability (van Duinen et al., 2015). The use of EUT in a drought disaster risk assessment model requires specifying one or more agent adaptation strategies, with associated costs and benefits under different drought impact scenarios. Agents choose the strategy with the highest (discounted-) expected utility, within their budget constraints. Expected utility is a function of the welfare, costs and benefits of the adaptation strategy. The assumption of perfect information in the EUT implies that the drought disaster risk perception of agents is identical to the actual drought disaster risk and thus can be fully predicted with objective drought disaster risk factors (van Duinen et al., 2015)

***BOX 3b*** *Prospect Theory (based on Schrieks, Botzen, Wens, Haer and Aerts, 2021)*

Prospect theory (PT) was developed by Kahneman and Tversky (1979) as a critique of EUT and then further developed by the same authors and renamed cumulative prospect theory (Tversky and Kahneman, 1992). EUT assumes that the utility of gains and losses is based on absolute wealth and that individuals assign equal weights to gains and losses. PT, on the other hand, assumes that people assess the utility of gains and losses as deviations from a reference point and that there are differences in preferences for gains and losses. Loss aversion in PT must be greater than 1, which means that losses have a bigger impact on the utility than equivalent gains. Moreover, PT takes into account non-linear, subjective probability weightings in risk decision making, which may differ across contexts and/or between individual agents (Barberis, 2013). Tversky and Kahneman (1992) find that people overweight low probabilities and underweight higher probabilities. As in the EUT, the adaptation measure is evaluated over the lifetime of the adaptation measure, and future periods are discounted to account for time preferences. The agent chooses the adaptation option that provides the highest expected utility within its budget, with the same budget constraint as in EUT.

***BOX 3c*** *Theory of Planned Behaviour (based on Schrieks, Botzen, Wens, Haer and Aerts, 2021)*

Theory of planned behaviour (TPB), developed by Ajzen (1991), is a psychological theory according to which the decision-making process of individuals and the intention to exhibit certain adaptive behaviour, is influenced by three factors (Ajzen , 1991 , 2002b). The first factor is attitude, which refers to the degree of personal, positive or negative, evaluation of behaviour. In the context of drought adaptation, these are agents' personal views on the importance and usefulness of an adaptation measure (Arunrat et al., 2016). The second factor is subjective norm, which refers to the perceived social pressure to carry out the behaviour, i.e., friends, neighbours, family or other people important to the agent expect them to invest in the adaptation measure (Yazdanpanah et al., 2014; Arunrat et al., 2016). The last factor is perceived behavioural control, which refers to an individual's belief in its own ability to carry out the intended decision (Yazdanpanah et al., 2014 ;Arunrat et al., 2016). The stronger the intention, the more likely the agent is to perform the adaptive behaviour. However, actual performance also depends on the availability of the necessary resources and skills, which Ajzen (1991) calls actual behavioural control.

***BOX 3d*** *Protection Motivation Theory (based on Schrieks, Botzen, Wens, Haer and Aerts, 2021)*

Protection Motivation Theory (PMT, Rogers, 1983) states that a person's intention to adapt depends on the threat (or risk) assessment and coping estimation (Maddux and Rogers, 1983; Rogers, 1983; Grothmann and Patt, 2005; Gebrehiwot and van der Veen , 2015). The risk assessment process consists of two sub-elements: the perceived probability and the perceived severity of the events being assessed. In the context of drought, perceived probability refers to one's expectation of the likelihood of being exposed to drought and perceived severity refers to the expected magnitude of the effects of the drought if the drought occurs (Keshavarz and Karami, 2016). The coping assessment depends on the belief in one's own ability to carry out the adaptation measure (perceived self-efficacy), the belief in the effectiveness of the adaptation measure (perceived response efficiency) and the perceived cost of the adaptation measure (Van Duinen et al., 2015a). A person's perception of the factors in both threat and coping values is influenced by personal characteristics and experiences and influences from the social network (Rogers, 1983). Rogers (1983) presents protection motivation, or intention to adapt, as an additive function of threat valuation and coping valuation, which can be translated into a linear function of intention to adapt for adaptation measures. The weights of the different variables depend on the context of the adaptation decision and can be estimated with statistical analysis of survey data.

### 3.3. An agent-based modelling setup

The primary tool for modelling individual adaptation decisions and complex interactions are agent-based models (ABM) (An et al., 2014; Gunkela & Külls, 2011; Patt & Siebenhüner, 2005). ABMs have been called the 'third way' of doing science, combining both an inductive and deductive approach (Matthews et al., 2007). Instead of describing the system in terms of variables, ABMs allow for the explicit simulation of probabilistic human decision making that responds to environmental states and other agents and who have the capacity to learn and adapt in response to changes in other agents (i.e., social influence) and the environment (i.e., drought disaster risk) (Matthews et al., 2007; Railsback & Grimm, 2012). Probabilistic functions describe individual-level behavioural dynamics of unique and autonomous agents, who give priority to their own objectives based on a set of internal (non-linear) rules (e.g., based on rationality, heuristics or learning) (Van Oel & Van Der Veen, 2011). The combined dynamics of these individual behaviours result in macro-scale consequences that drive changes to the system, hence allows us to predict the emergence of drought adaptation action and investigate its consequences (Berger, 2001; Jager & Janssen, 2012; Janssen & Ostrom, 2006; Schlüter & Pahl-Wostl, 2007).

ABMs may provide a greater insight into complex natural resource systems and their management, outperforming traditional approaches and thus can be helpful to address the complexities of the human - human – droughts interactions as identified in the field of socio-hydrology (Matthews et al., 2007).This capacity makes them an ideal tool to study feedbacks between society and the environment, and the emergence of drought prevention, mitigation or preparedness measures (Gunkela & Külls, 2011; Kelly et al., 2013; O'Connell, 2017; Schluter, Leslie and Levin, 2008; Walker et al., 2015 ). Where ABM approaches can also benefit the drought disaster risk community is in their ability to ingest results from economic (e.g., food market) and physical (e.g., hydrological or land use) models running on different time steps and scales, while producing results from socio-psychological behavioural models (Farjad et al., 2017; Kremmydas, Athanasiadis, & Rozakis, 2018). When coupled, these outputs can successively feed back into each other to generate spatially explicit, time-varying, human-influenced physical conditions (Bouziotas & Ertsen, 2017; Galán, López-Paredes, & Del Olmo, 2009; Mashhadi et al., 2017; Schreinemachers & Beressger, 2011). Given that ABMs can model heterogeneity in behavioural constraints, include social interactions, and transfer data between models (Berger & Troost, 2014), ABMs can be an effective tool to simulate the intertwined nature of heterogeneous adaptation decisions on each of the three risk determinants (Blöschl & Sivapalan, 2016; Khan et al., 2017; van Duinen et al., 2012a) (Box 4).

***BOX 4**: ABMs and drought disaster risk: Water stakeholders' behaviour*

ABMs can simulate the micro-level decisions of agents (e.g., farmers, governments, urban water users, cooperatives, institutions) and the interactions between them and their settings (e.g., social network and bio-physical environment) which result in emerging macro-scale adaptation dynamics (Kelly et al., 2013; Smajgl & Barreteau, 2017; Smajgl, Brown, Valbuena, & Huigen, 2011). Stakeholders' decisions are rarely completely rational or guaranteed to pursue the same objectives, making a centralized, top down, modelling approach unsuitable (Hyun, Yang, Tidwell, & Macknick, 2017). Modelling the water use of urban households, rural farmers, and local governments in ABMs should therefore be done in a bottom-up manner, through the creation of multiple agent types that each try to reach their individual goals by weighing off the utility of adaptation against the utility of no adaptation. This utility is often guided by a perceived risk, which is influenced by the agents' social environment, past experiences and risk memory (Di Baldassarre et al., 2017; Viglione et al., 2014).

PerceivedRiskt = w1 * PerceivedRiskt-1 + w2 * PastCropLosses + w3 * Isocialnetwork

The utility functions of different water stakeholders within a socio-hydrologic ABM can be adapted to include the influence of perceived drought disaster risk. For example:

Governments try to minimize societal losses caused by drought disasters by comparing the utility of adaption – such as investing in the building of a reservoir - with the utility of no adaptation, assuming that they have to cover the losses due to drought disasters in the form of emergency funds.

$$\text{Cost of Action} = \sum \text{U (Wealth} - \text{AdaptationCosts} - \text{PerceivedResidualRisk)}$$
$$\text{Cost of no Action} = \sum \text{U (Wealth} - \text{PerceivedRisk)}$$

Domestic water users try to minimize their water expenditures, which are dependent on their water use and the water price, the latter being influenced by drought disaster risk:

$$\text{Cost of Action} = \sum \text{U (Wealth} - \text{ReducedWaterUse} * \text{f(PerceivedRisk, WaterCost)} - \text{WaterEfficiencyInvestments)}$$
$$\text{Cost of No Action} = \sum \text{U (Wealth} - \text{WaterUse} * \text{f(PerceivedDroughtRisk , WaterCost)}$$

Farmers try to maximize their income by weighing their risk appraisal (the perceived likelihood of experiencing crop losses), the expected adaptation efficacy and the cost of the coping measures:

$$\text{Cost of Action} = \sum \text{U (Wealth} - \text{f(PerceivedRisk, Yieldloss)} + \text{AdaptationEfficacy} - \text{AdaptationCosts)}$$
$$\text{Cost of No Action} = \sum \text{U (Wealth} - \text{f(PerceivedRisk , Yieldloss))}$$

The implementation of adaptation measures by these actors will change actual and perceived risk in subsequent time-steps, therefore resulting in behavioural changes over time by simulating a learning process.

ABMs are not new to the domain of disaster risk (e.g., Poledna, Miess, & Thurner, 2018) nor to the domain of water resources research (e.g., Tesfatsion, Rehmann, Cardoso, Jie, & Gutowski, 2017). For example, Berger and Arnold presented the Mathematical Programming-based Multi-Agent Systems (MP-MAS) model which has since then been used to simulate land use change in agriculture and forestry systems and has been coupled with a variety of economic and environmental models to simulate crop yields, water supply, and individual decision-making (Berger & Arnold, 2006; Berger & Schreinemachers, 2009). In 2007, Schlüter & Pahl-Wostl demonstrated that ABMs are effective for exploring system characteristics and mechanisms of resilience in both decentralized and centralized water management systems. Schlüter et al. (2009), proposed an optimization ABM to study water allocation between multiple sectors in a semi-arid river delta. Variable water conditions were represented by average monthly flows perturbed by a random number. Gunkela & Külls (2011) investigated drought vulnerability and the decision-making process of the agents in a decentralised water supply system in Northeast of Brazil, while Van Oel and Van der Veen (2011) created an ABM to represent these complex interdependencies between human land use decision making and water availability over the Naivasha basin, Kenya.

Based on an empirical characterization of farmer behaviours, Dobbie (2013) simulated household decision making in rural Malawi to estimate food adequacy based on different policy scenarios. Akhbari & Grigg (2013) proposed an ABM linked to a continuous watershed model, that includes state, individual, and environmental stakeholders who act based on perceptions about the system, the environment, and each other; with the aim to study cooperative techniques for water sharing. Similarly, Mashhadi et al. (2017) assessed urban water sustainability for a community of households by coupling an ABM with hydrological models and climate change projections. Also, Koutiva and Makropoulos developed an urban water agent's behaviour model, to simulate domestic water users' behaviour in Athens, Greece (Koutiva & Makropoulos, 2016). Castilla-Rho et al. (2015) included multiple levels of decision making within an ABM, simulating interactions and feedbacks between institutional agents, water user associations and individual farmers to study managed groundwater systems and also Yu (2016) and Farhadi et al. (2016) demonstrated the ability for behavioural models to improve impact projections within dynamic management options, showcased by, respectively, the DistyriLake model for Lake Como, Italy and the agent-based-Nash model for the Daryan Aquifer, Iran. In a closer step towards a comprehensive socio-hydrologic, heterogeneous risk model, Van Duinen et al. conducted an empirical analysis of farmer drought adaptation, exploring the influence of risk perception and the role of social networks on agricultural technology adoption, including survey-based social network data within an ABM (van Duinen et al., 2012a, 2012b, 2015a, 2015b; 2016).

Most ABMs that explore drought or water scarcity do not explore risk dynamics and instead study how humans impact water resource systems. In many of these studies, human agents are treated as collectives rather than autonomous agents, and their influences in the system are not bidirectional, or structured in a way that facilitates the study of hazard, exposure and vulnerability (combined as risk). While an improvement over static conditions, such an approach is limited in its ability to study how climate dynamics and sustained drought conditions might alter adaptive behaviour and vice versa. Further, ABM literature reviews have shown that independent and ad-hoc assumptions continue to characterize decision processes within land-based human-environment ABMs (Groeneveld et al., 2017) and only few studies have implemented more complex behavioural theories when dealing with uncertain water availability (Barthel et al., 2008; Bouziotas & Ertsen, 2017), and fewer still have focused on risk (Barreteau et al., 2004; Blair & Buytaert, 2015).

The use of existing behavioural economic and psychological theories - calibrated with empirical methods - can improve the representation of heterogeneous, individual, bounded rational adaptive behaviour in agent-based models, but choosing which theory to apply to create the decision rules in the ABM is a challenge (Filatova et al., 2013; box 3a-d). The choice of a theory affects not only which factors are included in the simulation of the individual agent's decision-making process, but also how the interaction of this agent with other relevant agents and its environment can be modelled. The choice of theory should consider the purpose of the model and the local context of the modelled case (Schrieks et al.; box 5).

***BOX 5**: Comparing theories of adaptive behaviour under drought disaster risk (based on Schrieks, Botzen, Wens, Haer and Aerts, 2021)*

There is no single theory that covers all relevant decision variables. Which theory is preferable depends on the local context and the purpose of the model. In the context of adaptation to drought disaster risks, it is important to determine which types of actors should be included and which behavioural factors determine the adaptive behaviour of those actors. Table 2A compares four different theories, indicating the advantages and disadvantages of each.

In general, an advantage of economic theories is that they can be better linked to the natural hazard and risk assessment model. However, research shows that factors such as experience of previous droughts and individuals' sense of control are also important determinants of risk perception (van Duinen et al., 2015). The influence of these subjective risk perception factors has not been considered in economic theories. An advantage of psychological theories is that they can capture more heterogeneity in bounded rational beliefs, norms and personal attitudes. However, a challenge in their implementation in ABMs is that the original theories do not offer a mathematical formalisation (Schlüter et al., 2017; Mueller and Filatova, 2018): adaptation intention can be modelled (a) with probabilities, for example: the higher the intention to adapt, the more likely it is that the agent will actually invest in the adaptation measure (e.g. Keshavarz and Karami, 2016), or (b) with thresholds: agents will only invest if the intention to adapt is above a certain threshold (e.g. Hailegiorgis et al. al., 2018).

*Table 2A: Overview of theories*

| Theory | Advantages | Disadvantages |
|---|---|---|
| EUT | Full distribution of risk thus easy to link to hazard assessments and disaster risk assessments based on costs and benefits | Does not include psychological factors such as perceptions, attitudes and subjective norms; does not account for bounded rationality |
| PT | Full distribution of risk thus easy to link to hazard assessments; accounts for loss aversion and biased risk perception | Does not include psychological factors such as perceptions, attitudes and subjective norms |
| PMT | Combines risk perceptions and perceived costs and benefits of economic theories with individual coping perceptions | Does not include risk attitudes and time preferences; model includes subjective parameters that are hard to mathematically formalize. Proxy variables are needed to identify relative weights |
| TPB | Includes individual attitudes and subjective norms, thus includes influence of social network | Does not include risk perceptions, attitudes or time preferences; model includes subjective parameters that are hard to mathematically formalize. Proxy variables are needed to identify relative weights |

## 4. An agent-based socio-hydrologic framework for drought disaster risk assessments

With the understanding that individual adaptation influences drought hazard, exposure, and vulnerability dynamics, any model that does not account for these feedbacks will be suboptimal in simulating evolving risk. Given the discussion above, we argue that socio-hydrologic approaches and agent-based tools are a good way to support the exploration of drought adaptation pathways from alternative decision rules. In the remainder of this Chapter, we introduce a framework (figure 2.2) to integrate heterogeneous behaviour and physical models in a modelling space that is adaptable to different regions, data availability, and drought-based research questions.

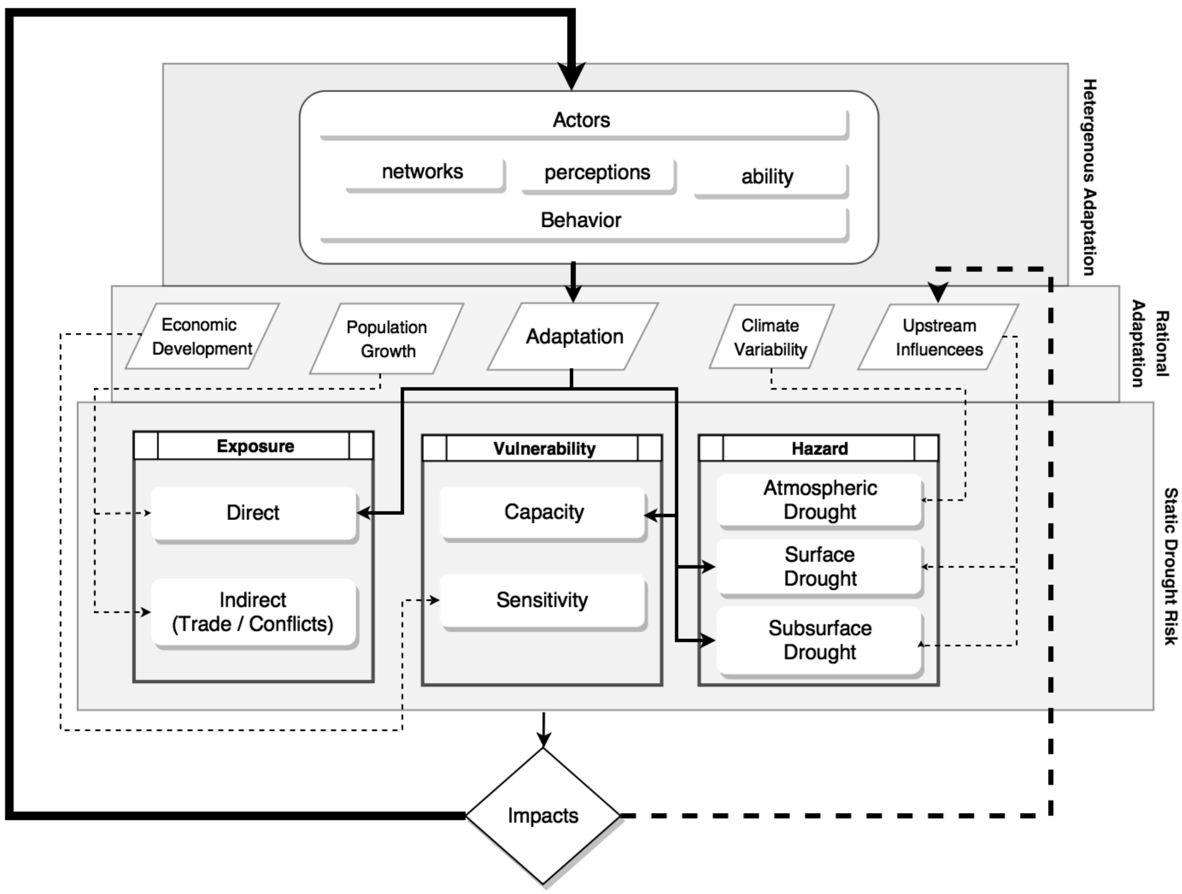



*Figure 2.2: Tiered framework proposing an agent-based socio-hydrologic approach for drought disaster risk modelling. The possible impact (i.e., disaster risk) of a drought drives an agent-based decision model (tier 3), in which autonomous agents respond to the perceived risk, considering their adaptation abilities and social network. Such agents make individual decisions and determine the set of adaptation measures implemented in the current time step. The combined effect of these adaptation measures is used as input (tier 2) into a water resource, hydrological, economic and/or land use model. Such models use data on climate variability, economic and population changes, and external forcing to calculate the current drought hazard, exposure, vulnerability and the possible impact (materialization of risk) (tier 1). The resulting impact will affect each agent's risk perception, serving as new input for the next time step. As such, impact calculation over time, i.e., risk assessment, is a dynamic process grounded in emergent adaptation decisions, a changing climate, and developing socio-economic conditions.*

### 4.1. Introducing the framework

The foundation of our framework is the traditional, static risk equation (UNISDR, 2015b), as presented in tier 1 of figure 2.2. In such an approach, anticipated impacts are a product of hazard, exposure and vulnerability, integrated over a specified time step. Depending on the research question, one or more suitable impact indicators and drought types can be selected.

To provide estimates for drought hazard, exposure and vulnerability in each time step, existing hydrological, water resource, land use and/or economic models can be used to generate time and space dependent estimates for drought hazard (physical water availability), exposure (land use, populations, and assets) and vulnerability (investment decisions, adaptation capacity). While outside a drought disaster risk context, a coupled ABM-hydrological (MODFLOW) model implementation can be seen in (Jaxa-Rozen, et al. 2019). ODD+D in Supplementary information such as census (e.g., as utilized in Bakker, Alam, van Dijk, & Rounsevell, 2014), meteorological observations or socio-economic datasets, are needed as input for these sub-models (Figure 2.2: dashed lines, tier 2) however these examples are simply options and are neither inclusive nor exhaustive. Instead, sub-model inclusion should be tailored to the region of interest and the phenomenon being studied. The impacts of rational adaptation are also included in tier 2, as drought management measures can be used as input for the risk calculations (bold lines).

Moreover, risk-model output can be used to drive changes in adaptation in a future time step (bold arrow), moving away from the prescribed, static realization of 'adaptation'. This feedback between water deficiencies and adaptation actions represents a socio-hydrologic approach (Sivapalan et al., 2012), where adaptation decisions depend on the past impacts experienced and influence the hazard, exposure and vulnerability in future time steps. These first two tiers and the bold arrow formulize the socio-hydrology approach with adaptation as a collective decision resulting from the human – drought disaster risk interaction (Elshafei, 2016).

In this Overview, we add a third tier to the modelling framework, which accounts for the heterogeneous adaptive behaviours of interacting, bounded-rational actors through an ABM approach (Malawska & Topping, 2016; Schlüter et al., 2017). In this set up, actors can make probabilistic decisions over the period of a time-step based on their adaptation ability, risk perception, and social network (Elagib et al., 2017; Farjad et al., 2017). The cumulative result of their adaptive behaviour can provide a more realistic, bottom-up realization of 'adaption', which in turn is used to calculate the current risk determinants in a heterogeneous way (tier 1). The resulting risk will influence each actor's individual risk perception, in the next time step (bold dashed line) (Di Baldassarre et al., 2017). This connection between actors, systems and risk makes the proposed approach a fully socio-hydrological, agent-based, model capable of capturing risk dynamics. Such a model would be able to simulate the social and environmental effects of bottom-up individual drought adaptation decisions, and heterogeneous responses to top-down interventions, across different timeframes and scales (Berger et al., 2017). As such, risk calculation becomes a dynamic process, which - grounded in emergent bounded-rational adaptation decisions and given variable bio-physical, hydrological and socio-economic conditions - allows to explore interactions between top-down and bottom-up strategies; upstream and downstream decisions; and between short-term and long-term priorities (Aerts et al. 2018).

### 4.2. Implementing the framework

To configure a model that utilizes this framework, research questions must be organized into domain, agent, and time spaces. The domain space would be represented by a gridded surface where each cell contains physical properties such as land cover, terrain, soil types, and river networks. In most ways this domain space (table 2.2) acts as a traditional environmental or hydrologic model which simulates the land-atmosphere interactions and surface/subsurface hydrology.

The agent space would be initialized with a set of (1) spatially explicit, (2) areal, and/or (3) external (non-spatial) agents. To describe an agent space, an example of an urban-rural interface will be outlined. **Spatially explicit agents** can include individual stakeholders (e.g., farmers who own, manage, and produce a cell or set of cells (see (Van Oel et al., 2019) for an example implementation using NetLogo software) (table 2). These agents are constrained by their physical domain (e.g., soil type, proximity to a river, etc.) but also influence the domain space through their management of the land (e.g., fallowed field, alfalfa production, or grape production). Additionally, agents can have their own set of attributes which can include things like financial savings, irrigation equipment, their social networks, and contractual agreements with government agencies. Most importantly, each agent is assigned a probabilistic set of behaviour rules that govern the way they make decisions when certain conditions arise in the domain space or other agents' behaviour.

**Areal agents** include those which act as collectives. An example of such an agent could be an urban population. This population would be defined by all urban cells in the domain space that use water as a collective. For example, the city could be assigned a density and a use rate that applies to each cell (e.g., a 10-cell urban extent with a density of 20 people per cell and a use rate of 50 gallons per person would equate to 10,000 gallons of use). Changes in areal agents would then be scalar and could include things like water restrictions (20% mandated reduction), seasonal use patterns (higher use in the summer), or alternative sources (desalinization). It is worth noting that this is just an example and that the same urban population could be designed as household-level, spatially explicit agents. Finally, **external agents** are those that do not reside in the domain space but introduce conditions, over which the spatially explicit and areal agents act on (top-down). Examples of external agents could include government agencies, irrigation districts, or environmental agencies (see Castilla-Rho et al., 2015 for a relevant overview of scales of decision-making and modes of interaction among water-management agents in a modelling set-up).

The final space in a coupled behaviour-physical model is the time space (table 2) as agents and the environment act on different time intervals. In our example, streamflow might be simulated daily, crop types might change annually, and urban extents might change biannually. Farmers make weekly irrigation, monthly harvesting, and annual investment decisions; irrigation districts make monthly allocations and yearly projections; and local governments make yearly decisions with respect to water pricing, environmental regulations, and well permitting. In the model space, all sub models must be resolved at a time step determined by the original sub-model codebase or by the author. The coupled model time steps must be configured in a way that information can be passed between models at the relevant time scale. Therefore, the primary cycles (e.g., daily, weekly, monthly, and yearly) must be identified, and within each, the appropriate agent sets must execute assigned decision routines based on the most up to date data from the most relevant time-space. When conceptualizing the construction of a model it is helpful to create a matrix of the time and agent sets that will be used and within each cell describe the behaviours and processes that will be addressed. An example of such a matrix for a model assessing drought disaster risk in the Central Valley of California is outlined in table 2.

*Table 2.2: Different types of agents that can be included when designing a socio-hydrologic agent-based model, an example created for the drought disaster risk context of California.*

| ***Agent*** | **Space** | **1 Daily** | **2 Weekly** | **3 Monthly** | **4 Yearly** |
|---|---|---|---|---|---|
| ***Environment*** | Domain | -Resolve energy and water balance<br>-Produce streamflow<br>Calculate soil states | | | |
| ***Farmer*** | Spatially explicit agent | -Operate Well | -Make irrigation decisions<br>-Work with other farmers<br>-Contract with irrigation district | -Make harvesting decisions<br>-Sell crops | -Make investment decisions<br>-Plant new crop<br>-Pay irrigation dues<br>-Build Well |
| ***Irrigation District managers*** | External agent | | | -Make water allocations | -Forecast next year's water contracts and pricing |
| ***Urban population*** | Areal agent | | -Use water on a seasonal basis | | -Change density<br>-Expand/Contract<br>-Change water sources |
| ***Government*** | External agent | | | -Approve well permits | -Assign water pricing for urban use<br>-Assign environmental flow regulations<br>-Impose any water limits<br>-Forecast Future conditions (NOAA/USGS) |

### 4.3. Challenges going forward

The proposed framework offers the opportunity to build on existing physical models and addresses many of the common challenges involved with modelling drought disaster risk (Elshafei et al., 2014; Blair & Buytaert, 2015). A few of these challenges, including droughts fuzzy edges and ambiguous starts, can be handled via spatially explicit agents and small time steps. Large spatiotemporal extents can be constrained by the modelling domain and human-influenced drought propagation can be handled through the modelling feedbacks from adaptation decisions and linked physical models. The drought teleconnection effect can be similarly included in the way a user defines feedbacks, parameterizes external agents, and carries impacts through the calculations. Most importantly, the framework is conceptualized to accommodate case studies and research questions ranging in size from a watershed to regional scales, and on time steps ranging from daily to annual (Li, 2016).

The primary challenges associated with the proposed framework stem from difficulties in data availability (Blair & Buytaert, 2015, 2016), model parameterization and validation (An, 2012; Grimm et al., 2006; Smajgl & Barreteau, 2017) and limited sensitivity testing methods (ten Broeke, Van Voorn, & Ligtenbergb, 2016). In larger models, computational demand (Castilla-Rho, Mariethoz, Rojas, Andersen, & Kelly, 2015b; Filatova, Verburg, Parker, & Stannard, 2013; Holman et al., 2018), and the necessity of implementing and managing a chain of complex models pose challenges that relate to model specific knowledge and computer and data science best practices.

With the understanding that all models are an abstraction of reality, the choice of where to spend development and computational efforts is important ( Troy et al., 2015). Depending on the research question, domain, and availability of resources, researchers can prioritize which parts of the framework should be modelled in most detail, what agents should be included and what input data is necessary (Blair & Buytaert, 2016; Sun et al., 2016). For example, one could choose to focus on a specific sector, a unique set of individual agents, social network representation, upstream vs. downstream effects, or economic trade issues. Another necessary choice requires balancing the trade-offs between spatial resolution and domain size. Linking ABMs with existing physical models can also require extensive data processing (pre and post) and/or binding various languages such as R, FORTRAN, NetLogo and MATLAB depending on the native formats and languages of the models selected ( de Bakker, de Jong, Schmitz, & Karssenberg, 2017). Depending on the choice of hydrological model and agent-based modelling language, two or more languages might need to be integrated, that cannot communicate with each other, hence shell scripts may be needed. The use of super-computing environments can help overcome some of these limitations but requires additional technical skill and knowledge such as parallelization, operating in a LINUX environment, and communicating large volumes of output data ( Berger & Troost, 2014).

Another challenge in adopting this framework is the selection of model time steps to deal with the time scale interactions (Elshafei, 2016; Sivapalan et al., 2015). Most agents (individuals, governments, urban users, institutions) make decisions on varying timescales that do not necessarily align with the timescales of physical processes (rainfall/runoff). Determining how to aggregate (or disaggregate) and/or harmonize varying timescales within a linear modelling framework is a necessary step in accurately integrating human and natural systems. Outside of purely technical limitations, researchers face a host of challenges related to model calibration and validation (Feola, Lerner, Jain, Montefrio, & Nicholas, 2015; Palmer & Smith, 2014). Companion or participatory modelling studies have proven successful in capturing behavioural dynamics of different agents across multiple sectors and at large scales, while online platforms can make such data collection more approachable, less time-intensive and more adaptable to multiple and wider spatial scales (Sušnik et al., 2018).

The inclusion of stakeholder groups at multiple stages in the model-building phase may be additionally useful in providing (expert) validation (Brown et al, 2016). One example of this is the work by Gober and the National Science Foundation's Decision Center for a Desert City, working with water resource managers, modellers, and government agents over the course of a decade to determine the factors and tools needed to build resilience in a desert city (Gober & Wheater, 2014). The use of social media data or other volunteered geographic information (Goodchild & Glennon, 2010) or mobile and other ICT data (Bell et al., 2018; 2016) can further provide insight towards behavioural patterns and preferences. While an interdisciplinary approach, inherent to socio-hydrological modelling, is often seen as a challenge because of conceptual, philosophical, or perceptual barriers, it also represents an increasingly recognized and urgent step towards the analysis of human-environment interactions (Kline et al., 2017).

## 5. Conclusion

This Overview highlights the need for including adaptation dynamics and their two-way feedback with drought hazard, exposure and vulnerability in drought disaster risk estimation. We hope this work contributes to the scarce literature regarding socio-hydrology and heterogeneous adaptive behaviour in drought disaster risk and that the proposed agent-based framework offers an outline towards dealing with the dynamic nature of human decisions and drought disaster risk. Further, we hope the proposed framework paints a clear picture for those looking to develop an ABM drought disaster risk model while also pointing out some of the hurdles one might encounter along the way. We emphasize this framework is not a solution in-and-of itself but rather a means to guide how an interdisciplinary research community might better model drought disaster risk and prioritize research moving forward. Including human behaviour in the calculation of drought disaster risk is certainly not an easy task. However, we hope to have convinced readers that the inclusion of emergent, adaptive behaviour is a necessary step towards better understanding human-risk interactions and evaluating drought disaster risk.

# CHAPTER 3:

## COMPLEXITIES IN DROUGHT ADAPTATION BEHAVIOUR:

## *AN ANALYSIS OF SMALLHOLDER FARMERS IN KENYA*

*This Chapter is published as:*

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## Samenvatting

Kleine agrariërs in semi-aride gebieden worden voortdurend geconfronteerd met droogte episodes die leiden tot terugkerende gewasschade, inkomensverlies en voedselonzekerheid. Deze agrariërs nemen adaptieve maatregelen om met dit risico om te gaan. Door empirische gegevens en bestaande gedragstheorieën te vergelijken en te combineren, bestudeerden we de complexiteit van het aanpassingsgedrag van kleine agrariërs in Kitui, Kenia. We hielden interviews met sleutelinformanten, een enquête onder rampenmanagers en een uitgebreide vragenlijst- en keuze-experiment onder lokale kleine agrariërs, en ontdekten dat wantrouwen in voorspellingen en een sterk geloof in God barrières voor aanpassing bleken te zijn, terwijl lid zijn van een landbouw coöperatie en het al genomen hebben van eerdere aanpassingsbeslissingen, de intentie om nieuwe maatregelen te nemen leken te stimuleren.

Onze resultaten bevestigen het belang van verschillende componenten van bestaande gelimiteerd rationele theorieën, in die zin dat risico-inschatting, sociale norm, zelfeffectiviteit en responskosten en -effectiviteit een significante invloed hebben op het de beslissingen over droogtemaatregelen. Geen van de geëvalueerde theorieën kon echter het waargenomen gedrag volledig verklaren. Voorts tonen wij aan dat aangepaste trainingen, verbeterde systemen voor vroegtijdige waarschuwing, financiële steun vóór een droogte en kredietregelingen met lage rente, de intentie om zich aan te passen aan het droogterisico, vergroten. Hoewel een algemene afkeer van de huidige beleidssituatie duidelijk is, is er grote heterogeniteit in de voorkeuren voor bovenstaande beleidsmaatregelen. De resultaten van deze uitgebreide gegevensverzameling en -analyse kunnen worden gebruikt om de meest kwetsbare groepen te identificeren en een doelgericht aanpassingsbeleid te ontwikkelen, en voor het ontwerpen, kalibreren en valideren van mathematische functies om heterogene aanpassingsbeslissingen in dynamische droogterisicomodellen te modelleren.

**Summary**

Smallholder farmers in semi-arid regions continuously face drought disaster risk, leading to recurring crop damage, income loss and food insecurity, and they are taking adaptive measures to cope with this risk. By comparing and combining empirical data and existing behavioural theories, we studied the complexity of smallholder farmers' adaptive behaviour in Kitui, Kenya. We conducted interviews with key informants, a survey of disaster managers and an extensive questionnaire and choice experiment among local smallholders and found that mistrust in forecasting and a strong belief in God appeared to be barriers to adaptation, while farm groups and past adaptation decisions seemed to stimulate the intention to adopt new measures.

Our results confirm the importance of several components of existing bounded rational theories in that risk appraisal, social norm, self-efficacy and response cost and efficacy significantly influence adaptive behaviour under drought disaster risk. However, none of the evaluated theories could fully explain the observed behaviour. We further demonstrate that tailored extension services, improved early warning systems, ex-ante cash aid and low interest credit schemes increase the intention to adapt. While a general aversion to the current situation is evident, there is great heterogeneity in the preferences for these policies.

Findings of this the extensive data collection and analysis can be used to identify the most vulnerable groups and develop well-targeted adaptation policies, and for designing, calibrating and validating of utility functions to model heterogeneous adjustment decisions in dynamic drought disaster risk models.

## 1. Introduction

Increasing climate variability and changing socioeconomic conditions exacerbate the frequency and intensity of drought disasters, aggravating local food insecurity and dependency on external food aid in agriculture-dependent regions (Kenya, 2013; Khisa, 2017; Khisa & Oteng, S., 2014; Ochieng et al., 2016). Given these challenges, the adoption of drought adaptation measures is critical to reduce existing and future drought disaster risk, particularly for smallholder farmers in low- and middle-income countries (UNDP et al., 2009). From a socio-hydrological perspective, unravelling the adaptive behaviour of people responding to changing environmental and social conditions is a way to improve the assessment of current and future drought disaster risk (Blair & Buytaert, 2016; Di Baldassarre et al., 2019; Montanari, 2015; Sivapalan et al., 2016). Insight into this co-evolution of human adaptation and drought disaster risk is vital to the evaluation of future drought impacts and the development of any disaster risk reduction strategy (Barthel et al., 2008; Eiser et al., 2012), (Blauhut et al., 2015). There are different models which can be applied to capture socio-hydrological feedbacks, such as agent-based models or system dynamics models, that allow to model drought disaster risk in a dynamic way (Chapter 2). However, such models need an elaborated description and quantitative information on the drivers and barriers of the adaptation decision process.

While ample of empirical studies try to uncover the relation between socio-economic, political and environmental variables and (past) adaptation, there is little scientific agreement on which factors influence decisions on water harvesting measures and other climate-smart agricultural practices (Bhavnani et al., 2008; Mwaluma & Mwangi, 2008; UNISDR et al., 2009)(UNISDR et al., 2009). One can observe that risk reducing measures are often taken after disasters occur, and since adaptation can alter the likelihood of future impacts, this can in turn affect forthcoming human decisions (Baldassarre et al., 2015). However, there are barely any longitudinal surveys to evidence the cause-effect relationships, to really understand the underlying processes behind the relations between such variables (Waldman et al., 2020) . Moreover, the choice of investigated factors often seems rather eclectic—it remains unclear whether all relevant cognitive-behavioural processes were included in many of these studies (van Duinen et al., 2015b). Both reverse causality and omission can result in a biased estimation of the effects and lead to inaccurate interpretation (Troy et al., 2015). The use of a psychological or economic theory in the data collection process can create a solid base to discuss behavioural factors, and it also supports asking the right questions (Waldman et al., 2020). Linking theory with observations allows for a better generalisation of the quantified link between drivers/barriers and the adaptation response, which is necessary when one's aim is to draw conclusions on future behaviours and challenge the wide applicability of these results in different case studies (Schlüter et al., 2017). Only then can this information be used to describe the decision rules and structure of dynamic drought disaster risk models that are able to capture the intertwined nature of drought impacts and adaptation.

In this manuscript, we evaluate different types of survey data about the drivers and barriers of adaptation, in the light of existing behavioural theories. Zooming in on the case of smallholder farmers in Kitui, Kenya, we analyse the heterogeneity of individual adaptive behaviours under drought disaster risk. The data was collected using commonly employed, complementary techniques: interviews, fuzzy cognitive mapping, semi-structured questionnaires, and discrete choice experiments. These methods were designed to evaluate the applicability of existing behavioural theories to the case of Kitui, a semi-arid agro-pastoral area in Kenya. Therefore, the research presented in this Chapter adds to the available empirical data describing factors that motivate smallholder farmers to (not) implement drought adaptation measures but is novel as it combines multiple empirical methods while also being grounded in renowned economic and psychological theories. Our aim is to support a better understanding of processes that shape farmers' adaptation to drought disaster risk, and to creating a knowledge base that can be used to calibrate and validate dynamic drought disaster risk models.

The remainder of this Chapter is organized as follows: Section 2 introduces the case study area in Kenya. Section 3 provides an overview of potential drivers for adaptation decisions by smallholder farmers and related behavioural theories. Section 4 outlines the methods used to collect empirical data on adaptive behaviour while section 5 contains the results of these different data collection methods. Section 6 presents an overview of the empirically and theory-supported drivers for drought adaptation among smallholders, linking empirical observations with existing behavioural theory, and Section 7 concludes.

## 2. The Kitui study area in semi-arid Kenya

Food production in Kenya heavily depends on smallholder rain-fed agriculture; however, farmers are challenged to match the erratic rainfall with crop water requirements (Government of Republic of Kenya, 2014; Omoyo et al., 2015). Droughts are the most frequently occurring natural hazard in Kenya, causing devastating and pervasive socioeconomic impacts every 4 to 5 years (Alessandro et al., 2015; KEFRI et al., 2014; Kioko, 2013). In Kitui County, in the southeast of Kenya, water availability is the preeminent factor for socioeconomic development. Water resources in this semi-arid county are scarce, unevenly distributed, and often unpredictable. The county receives approximately 1000 mm of rainfall per year, of which almost all falls erratically during two rainy seasons: March–May, and October–December (K. P. C. C. Rao et al., 2011). Kitui is seen as highly vulnerable to drought disasters (UNDP, 2007, 2012) as most of the water that can be used for domestic or irrigation use comes from ephemeral rivers which largely fall dry during the dry season. With less than 20% of the population having access to piped water – mainly households living in the towns-, woman and children of rural farmers travel approximately 8 km in regular years to fetch water or up to 15 km on foot during prolonged droughts (County Government of Kitui & Kitui County, 2013).

Kitui county is labelled as a marginal farming zone; most rural people are subsistence crop and livestock farmers (Khisa, 2018). The main source of income is rain-fed agricultural production, and irrigation is only possible close to rivers or with expensive groundwater wells (Lasage et al., 2008). Maize, the main staple crop of the region, is grown by most farmers but is quite vulnerable to water shortages. A changing climate has already led to more frequent and longer droughts, which is also perceived as a worsening situation by Kitui smallholder farmers (Khisa, 2017, 2018; Mutunga et al., 2017). Having frequently experienced climate-related crop failures, the farmers in the area have a long history of adapting to drought disasters (for examples of measures, see table 3.1).

While water harvesting systems and climate smart agricultural practices can reduce a household's vulnerability to drought by 40% (Schoderer & Lasage, 2017), the adoption of these proactive drought disaster risk reduction strategies has remained surprisingly low (Below, Artner, Siebert, et al., 2010; Bryan et al., 2013a; Epule et al., 2017; Erenstein et al., 2011; Kimani et al., 2015; Oremo, 2013; Recha et al., 2012; Venzi, Mulwa, 2015). Okumu et al. demonstrated that, while droughts were acknowledged to be the main cause of food insecurity (96% of respondents) and seem to have prolonged over time (55% of respondents), only 15% of respondents in Kitui had adopted water harvesting measures (Oremo, 2013). This was confirmed by Khisa et al., who reported that 74% of respondents did not employ any strategy to prepare for the effects of climate change (Khisa & Oteng, 2014). The high level of poverty in Kitui, estimated at 47.5% compared with the national average of 36.1%, is both a cause and consequence of this limited adaptation to climate change and extreme events (Kitui County, 2018).

*Table 3.1: Drought adaptation measures against drought impact taken by farmers in Kitui County, Kenya (based on household survey data 2000, 2004. 2007, 2010 by the Tegemeo Institute, 2004, 2007, 2010))*

| ***Measures*** | **Description** |
|---|---|
| ***Fanya-Juu*** | Terraces formed for easier cultivation and prevention of soil erosion. |
| ***Zai-pit*** | Dug pits in the soil during the preseason to catch water and to concentrate compost. |
| ***Cistern / tank*** | A waterproof receptacle for holding liquids, in this case, water. |
| ***Shallow well*** | A well is a hole that has been dug, bored, driven or drilled into the ground for the purpose of extracting water. A shallow well is approximately 7-15 meters deep. |
| ***Mulch*** | Mulch is a layer of material applied to the surface of soil to conserve soil moisture, and to improve the fertility and health of the soil. |
| ***Irrigation*** | Irrigation infrastructures are technologies that assist in the spreading of water onto crops. |
| ***Conservation agriculture*** | Conservation agriculture is a farming system used for minimum soil disturbance, maintenance of a permanent soil cover, and diversification of plant species. |
| ***Stone terraces*** | Traditional simple cultivation technology used in dry areas and/or sloping land. |
| ***Farm pond*** | A water harvesting structure that can also be used for fishing |
| ***Roadside harvesting*** | A water harvesting structure. To collect runoff from the roads |
| ***Hybrid crop varieties / diversification*** | Drought tolerant or short cycle varieties of the main staple crops (maize, beans) or varying the amount of crop types per year |
| ***Adding manure*** | Soil fertility influences the water holding capacity of the farmland, diversification |

# 3. Identifying factors influencing drought adaptation decisions of smallholder farmers

## 3.1. Empirical drivers of and barriers to adaptive behaviour

With perfect awareness of future drought disaster risk, flawless early warning systems, and without socioeconomic limitations, people would be able to make proactive, rational decisions and achieve optimal economic drought disaster risk management (Waldman et al., 2020). However, assumptions about perfect information and sufficient investment capacity do not hold when examining real-world empirical adaptation responses (Gigerenzer & Goldstein, 1996; Kremmydas et al., 2018; Malawska & Topping, 2016; Schlüter et al., 2017). Adaptation decisions are often steered by stakeholders' risk perception, experiential factors, feelings of dread or worry, perceived self-efficacy, and perceived behavioural control, which all introduce a bias to rational economic decision making (Asayehegn et al., 2017; Bouziotas & Ertsen, 2017; Kahneman & Tversky, 1979; Kasperson et al., 1988; Maddux & Rogers, 1983; Slovic, 1987; Sutton, 2001; van Duinen et al., 2016). A growing body of research aims to understand the factors influencing the choice to adopt adaptation measures (Deressa et al., 2009). Here, we present relevant review studies on the drivers of drought adaptation by farmers in Africa, and some specific studies relevant for Kenya and its Kitui region, summarized in Table 3.2.

Research on climate change adaptation practices in Africa shows that the characteristics of the proposed technology (e.g. gain, costs, maintenance, distance to markets), farmers attitude towards risk and climate change perceptions, knowledge (e.g. through social networks, farmer groups or extension services), institutional support, and the financial (e.g. distance to markets, access to credit markets) and policy (e.g. security of land holdings) environment are important drivers of adoption of adaptation measures (Below, Artner, Sieber, et al., 2010; Below et al., 2012; Gbegbelegbe et al., 2018b; Shikuku et al., 2017). Also socio-demographic characteristics such as household size, sex and age of the household head appear significant (Shikuku et al., 2017). Scientists focussing on Kenyan farmers specifically found similar drivers and barriers to adaptation, adding socio-economic factors such as poverty, off-farm income, farm expenditure, food expenditure and human capital to the list (Bryan et al., 2013c; Ifejika Speranza et al., 2008; Muhammad et al., 2010b; Murgor et al., 2013; Tongruksawattana, 2014). Research from Kitui confirmed these factors, but also mention distance to water sources, farming experience, access to forecasts, and influence of social network as important for the decision whether or not to adapt to drought disaster risk and climate change (Eriksen & Lind, 2009; Evelyn & Charles, 2018; Khisa & Oteng, 2014; Omoyo et al., 2015; Owuor et al., 2005).

In general, the adaptation response of farmers to drought or climate change is found to be heterogenic in time and space (van Duinen et al., 2016). However, with regression analyses - commonly applied in the cited studies – the heterogeneity in behaviour and the cognitive processes behind the found relationships are not always explored, hindering the use of the results when one's aim is to draw conclusions on future behaviours or to model drought disaster risk in a dynamic way. Furthermore, while knowledge/skills, assets/market, and risk perception are cited as dominant factors, different drivers of and barriers to adoption appear more or less significant in different case studies. The absence of theories to frame such results challenges their use in other case studies because generalizing them requires making multiple assumptions that are hard to substantiate.

*Table 3.2: Factors influencing adaptation decisions, investigated in literature about Eastern Africa, climate change and drought disaster risk adaptation.*

| DRIVERS | References (non-exhaustive list of Sub-Saharan reviews and Kenyan case studies) |
|---|---|
| ***NATURAL CAPITAL*** | |
| ***Land ownership, tenure security*** | Muhammad et al 2010 Speranza 2010 Owuor 2005 Bedeke 2019 Below 2012 Gbegbelebge 2017 Di Falco 2014; de Jalon et al. 2018 Mtakwa 2015 |
| ***No access to water, long distance*** | Okumu 2013 Nthenge 2016 Oromo 2015 Khisa 2014 |
| ***Larger field size, flatness of soil*** | Muhammad et al 2010 Nkatha 2017 Villaneuva 2016 Gbegbelebge 2017 Bryan et al. 2013 Tongruksawattana 2019 Arslana 2014 |
| ***FINANCIAL CAPITAL*** | |
| ***No shortage of assets*** | Muhammad Et Al 2010 Nkatha 2017; Speranza 2010 Nthenge 2016 Okumu 2013 Oromo 2015 Khisha 2014 Owuor 2005 Villaneuva 2016 Gbegbelebge 2017 Tongruksawattana 2019 Shikuku 2017 Bryan Et Al. 2013 Mtakwa 2015 |
| ***More external, off-farm income*** | Nkatha 2017 Bedeke 2019 Bryan et al. 2013 Bryan et al. 2013 Muhammad et al 2010 |
| ***Aid, remittances*** | Nkatha 2017 |
| ***Access micro credit / loans*** | Muhammad Et Al 2010 Nkatha 2017; Speranza 2010 Khisa 2014 Mutunga 2017 Matere 2016 Bedeke 2019 Holden 2017 Below 2012 Gbegbelebge 2017 Tongruksawattana 2019 Shikuku 2017 Bryan Et Al. 2013 |
| ***Larger Animal stock*** | Speranza 2010 Owuor 2005 |
| ***Radio, bike, phone*** | Muhammad et al 2010 Owuor 2005 Arslana 2014 |
| ***Having a stable food security*** | Muhammad et al 2010 |
| ***HUMAN CAPITAL*** | |
| ***Having Labour power*** | Muhammad et al 2010 Nkatha 2017 Nthenge 2016 Senyolo 2018 villaneuva 2016 |
| ***Hiver Education, literacy*** | Nkatha 2017 Okumu 2013 Mwangi et al 2015 Oromo 2015 Bedeke 2019 Below 2012 Tongruksawattana; Bryan et al. 2013 de Jalon et al. 2018 Mtakwa 2015 |
| ***Access to extension training, farmer field school*** | Muhammad et al 2010 Nkatha 2017 Nthenge 2016 Okumu 2013 Mwangi et al 2015 Oromo 2015 Khisa 2014 Mutunga 2017 matere 2016 Bedeke 2019 Mfitumukiza1, Below 2012 Bryan et al. 2013 Tongruksawattana 2019 Arslana 2014 Shikuku 2017 Di Falco XXX; |
| ***Agricultural support*** | Nkatha 2017 |
| ***Farm experience*** | Nkatha 2017 Mwangi et al 2015 Oromo 2015 Bedeke 2019 Bryan et al. 2013 Shikuku 2017 |
| ***Health*** | Okumu 2013 |
| ***Household size*** | Bryan et al. 2013 Shikuku 2017 |
| ***Planning skills*** | Gbegbelebge 2017 |
| ***Agricultural skills*** | Speranza 2010 Mwangi et al 2015 Drechsel 2005 Bryan et al. 2013 Mtakwa 2015 |
| ***SOCIAL CAPITAL*** | |
| ***Membership association*** | Muhammad et al 2010; Nkatha 2017 Bedeke 2019 Gbegbelebge 2017 Tongruksawattana Shikuku 2017 |
| ***Gender (being male)*** | Muhammad 2010; Nkatha 2017 Mwangi et al 2015 Bedeke 2019 Shikuku 2017 |
| ***Neighbours, social capital*** | Khisa 2014 Bedeke 2019 Below 2012 Drechsel 2005; de Jalon et al. 2018; Wossen 2013 |
| ***INFRASTRUCTURAL CAPITAL*** | |
| ***Institutional support*** | Nthenge 2016; Gbegbelebge 2017 Drechsel 2005 Di Falco XXX |
| ***Access to input markets*** | Muhammad et al 2010 Nkatha 2017 Oromo 2015 Khisa 2014 Below 2012 Drechsel 2005 Bryan et al. 2013 |
| ***Access to output markets*** | Muhammad et al 2010; Speranza 2010 Oromo 2015 Bedeke 2019 Arslana 2014; Below 2012 |

| | |
|---|---|
| ***Good Infrastructure*** | Owuor 2005 |
| ***PERCEIVED CLIMATE TRENDS*** | |
| ***Access to Climate info services*** | Mutunga 2017 |
| ***Not believing in GOD as saviour*** | Center for Science and technology innovation 2009 |
| ***Perceiving drought to be frequent and severe*** | Muhammad et al 2010 Rao 2011 Holden 2017 Below 2012 Tongruksawattana 2019 Arslana 2014 Shikuku 2017; Drechsel 2005 |
| ***Awareness of climate change*** | Center for science and technology innovation 2009 Villaneuva 2016 Arslana 2014; Drechsel 2005 |
| ***Low risk averseness*** | ; Nkatha 2017 Holden 2015 Holden 2017; Drechsel 2005 |
| ***MEASURE Characteristics*** | |
| ***Yield variability*** | Muhammad et al 2010 Shikuku 2017 |
| ***Awareness of benefits*** | Villanueva 2016 Drechsel 2005 |
| ***Cost effectiveness of the measure*** | Nkatha 2017 Mwangi et al 2015 Muhammad et al 2010; Drechsel 2005 |
| ***Positive perception of technology*** | Nkatha 2017 |

### 3.2. Existing theories on adaptive behaviour

A commonly used economic model for decision making under uncertainty is the (subjective) Expected Utility Theory, which is based on the supposition that people can make rational choices (allowing for biased risk knowledge) and choose the option with the highest utility (Morgenstern & Neumann, 1953; Cerreia-Vioglio et al., 2013). Such utility maximizing theories, however, assume people have perfect knowledge on the probability of shocks as well as the costs and benefits of actions, and ignore the complexity of human adaptation decisions: emotional, psychological, and social factors – along with objective arguments – affect individuals' evaluation of drought, leading to imperfect judgement (Findlater et al., 2019; Waldman et al., 2020). Observed adaptive behaviour in the face of disaster risk is found to be bounded rational and heterogeneous in time and space; smallholder farmers tend to look for satisfaction rather than utility maximisation when making relevant decisions about their farm water management in the face of droughts (Ardalan et al., 2015; Gigerenzer & Goldstein, 1996; Simon, 1997). Table 3.3 describes the behavioural factors used in existing socio-cognitive theories that aim to describe the decision-making process of humans based psychological and economical sciences. Other adaptive behaviour theories link economics to psychological and sociological sciences. Examples of more complex theories about adaptive behaviour are the agricultural adaptation and perception model (Below et al., 2015), the trade-off analysis model for multi-dimensional impact assessment (Claessens et al., 2012), the Consumat approach (Jager & Janssen, 2012), the technology acceptance model (Szajna, 1996), Rogers' innovation diffusion model (Rogers, 1962), the prospect theory (Kahneman & Tversky, 1979), the protection motivation theory (Maddux & Rogers, 1983), the socio-cognitive model of private proactive adaptation to climate change (Grothmann & Patt, 2005), the value-belief-norm theory of environmentalism (Stern et al., n.d.), and the theory of planned behaviour (Madden et al., 1992; Sutton, 2001).

Empirical evidence is required to validate these behavioural theories, translate them into measurable characteristics of farm households, and formalise them in quantitative terms. Only few authors have empirically quantified the link between drivers and drought adaptation intentions through the use of a theoretical decision-making framework, thus overcoming the gap between case-specific empirics and generalisable theory—in most cases the Protection Motivation Theory, and sometimes the Theory of Planned Behaviour (e.g., Dobbie, 2013; Gebrehiwot & van der Veen, 2015; Keshavarz & Karami, 2014, 2015, 2016a; Stefanovic, 2015; Zeweld et al., 2017; Zheng & Dallimer, 2016). While multiple studies outside of Kenya have successfully applied the Expected Utility Theory and PT (e.g., Asgary & Levy, 2009; Holden & Quiggin, 2017b), Bryan (2013) did not find strong evidence to support those theories for climate change adaptation behaviour of Kenyan farmers. Several studies on smallholder farmers have applied the Theory of Planned Behaviour (e.g., Joao et al., 2015; Senger et al., 2017; Willy & Holm-Müller, 2013), but for example Niles et al. (2016) did not find empirical evidence to support the theory among farmers in drought-prone New Zealand (Niles et al., 2016).

*Table 3.3: Schematic overview of behavioural factors used in existing socio-cognitive theories*

| THEORY | BEHAVIOURAL FACTORS INCLUDED IN THE THEORY | | | | |
|---|---|---|---|---|---|
| **Trade-Off Analysis Model** | feasibility of the measure | costs of the measures | | | |
| **Consumat Theory** | repetition, imitation, inquiring, optimising | needs satisfaction | experienced uncertainty | behavioural control | |
| **Agricultural Adaptation And Perception Model** | vulnerability | livelihood trends | climate impacts | climate perception | potentials and obstacles |
| **Technology Acceptance Model** | perceived usefulness (subjective norm, output quality, result demonstrability, …) | perceived ease of use (experience, voluntariness) | | | |
| **Rogers' Innovation Diffusion Model** | relative advantage | compat ibility | complexity | trial ability | observability |
| **Prospect Theory** | financial costs | financial gains (avoided loss) | risk averseness | | |
| **Protection Motivation Theory** | risk appraisal (perceived frequency, severity) | coping appraisal (adaptation costs, efficacy, self-efficacy) | | | |
| **Value-Belief-Norm Theory Of Environmentalism** | values (altruism, worldview, egoism) | beliefs (consequences, perceived ability) | personal norms (sense of obligation) | | |
| **Theory Of Planned Behaviour** | subjective norm | attitude | perceived behavioural control | | |

The Protection Motivation Theory yielded more successes in explaining empirically observed adaptation decisions; Dang et al. (2014) demonstrated its application for private adaptive measures to climate change among rice farmers in the Mekong Delta, Vietnam (Le Dang et al., 2014, Van Duinen et al. 2012, 2012a) followed the theory investigating social networks and farmers' adoption of irrigation infrastructure in The Netherlands, and Keshavarz and Karami (Keshavarz & Karami, 2015, 2016b) illustrated that the theory, in combination with farmers' social environment significantly influenced pro-environmental behaviour under drought in Iran. Zooming in on Africa and Kenya, both Regasa et al. (2019), Hailegiogris et al. (2018) and Gebrehiwot and Van der Veen (2015) successfully used the Protection Motivation Theory to describe the socio-cognitive behaviour of rural households toward climate change and droughts in Ethiopia (Hailegiorgis et al., 2018; Regasa & Akirso, 2019a; Gebrehiwot & van der Veen, 2015). Moreover, Stefanovic (2015) found the Protection Motivation Theory provided a solid background to explain the socio-cognitive-behavioural processes influencing climate change adaptation among smallholder farming systems in Kenya (Stefanovic, 2015). Therefore, in the presented research, the Protection Motivation Theory received special attention and was used to frame the data collection process. However, also additional factors regarding adaptive behaviour (from other theories or empirics) were investigated because they could approve or disprove the applicability of these theories for the Kitui case study.

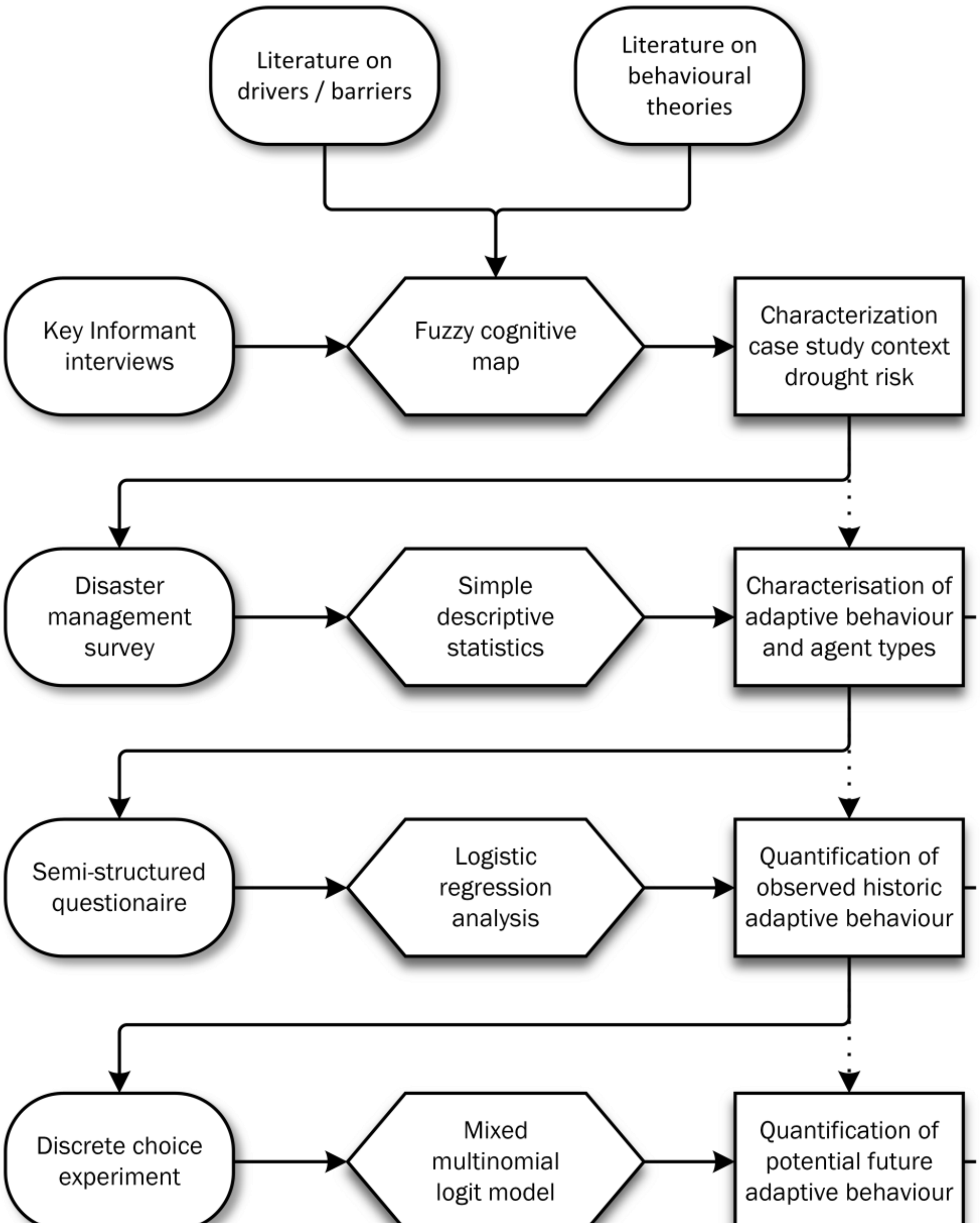


*Figure 3.1: Flow diagram showing literature overview (top row), data collection (left column) and data processing (diamond shapes) activities done to describe, qualitatively and quantitatively, the adaptive behaviour of smallholder farmers under drought disaster risk in Kitui (squares) done in this research with the eventual purpose to calibrate and validate adaptation dynamics in dynamic drought disaster risk models.*

## 4. Data collection and processing

Information on drought adaptation, farm characteristics, potential policies, risk perceptions, and various other potential drivers and barriers to adaptation decisions (van Duinen et al., 2015d) was collected in a participatory manner (Janssen & Ostrom, 2006; Smajgl & Barreteau, 2017). The survey methods and designs were supported by existing literature (Section 3) and follow the recommendations of Hailegiorgis et al 2018, and Smajgl et al., 2011 regarding collecting data for quantifying behavioural rules. Four methods) were applied in the research for this Chapter: interviews with key informants, a structured questionnaire among disaster managers, a semi-structured questionnaire among farm households, and a choice experiment among farm households. Figure 3.1 presents a flow diagram illustrating the four data collection and data processing methods that were applied to qualitatively and quantitatively describe the adaptive behaviour of smallholder farmers under drought disaster risk in Kitui. They are elaborated in the following subsections.

### 4.1. Key informant interview design

Relevant key informants (see Appendix Table 3A) were consulted to provide their view on the most important drought disaster risk measures, drivers for adaptive behaviour, and issues that limit the adoption of said measures. All key informants were dealing directly or indirectly with the agricultural impacts of droughts and were experienced in the field of water management in Kitui or Kenya. First, five 'example farmers' were interviewed about their experience of searching for knowledge and money to invest in certain drought adaptation measures as well as their experience of showcasing their climate-smart farm practices to other farmers. The opening question for these interviews was as follows: "If we wanted to predict which farmers are going to adopt new adaptation measures in the next season and which are not, which information about these farmers do we need and what do you think are the most important drivers and barriers for them?" Additionally, local and national stakeholders were asked to participate in a fuzzy cognitive mapping exercise centred around this question. Fuzzy cognitive mapping, a combination of fuzzy logic and cognitive mapping, is a participatory technique to find cause-effect relations between environmental and social variables in data-scarce conditions (Giordano & Vurro, 2010; Singh & Chudasama, 2017b).

Aiming to sketch the drought disaster risk system and the perceptions of the participants thereof, participants were individually asked to cite and draw lines between the detected root causes, existing dynamic pressures, and observed vulnerabilities to the adoption of drought adaptation and drought disaster risk. We started from white sheets to prevent participants being influenced by existing theories or drivers/barriers mentioned by previous participants (Murungweni et al., 2011), and collected all concepts mentioned by the participants (called nodes) and all causal relations (called connections) in one overview schedule. By combining the information from all interviews and grouping them according to factors from the existing theories, the main links and interactions between drivers and barriers that affect the risk and adaptation were visualised in a schematic overview (Appendix figure 3A). Marking concepts in bold if they were seen as key concepts by multiple stakeholders, the overview provides a macro—level, qualitative view of the drought disaster risk system in Kitui (similar to (Bunclark et al., 2018; Giordano et al., 2005; Mehryar et al., 2019a, 2019b)).This bottom-up, participatory approach provided a first insight of which causes and effects matter most in the Kitui context, and to refine or refute initial assumptions related to the adaptive behaviour of farmers; information which was used to shape the questions for the consecutive disaster management survey (4.2) and the household survey (4.3).

### 4.2. Disaster management survey design

A short, eight-question survey among African disaster management officers was executed to obtain input from policymakers and disaster risk reduction experts. The survey reached 54 Sub-Saharan African disaster managers from 9 different countries, of whom 8 were from Kenya. 28 worked on national planning and policy, 4 on local planning and policy, 10 on local civil protection and disaster response, and 12 on local education and raising awareness. They were contacted over email through an existing network of disaster risk management (over 150 recipients), but participation was anonymous. The top-down view of these disaster managers – Kenyan or other - on the limitations for the adoption of drought adaptation is insightful as their policies are based in such information – and teaches us something about the potential generalizability of the adaptive behaviour of smallholder farmers, beyond the case study.

Given the promising results in studies on the Protection Motivation Theory, and the Protection Motivation Theory factors' appearance in the key informant interviews (4.1), factors of this sociocognitive model of proactive private adaptation were explicitly included in the questions. Moreover, questions related to "subjective norm" that is, normative beliefs or perceived social pressure by the farmer network, -a factor of the Theory of Planned Behaviour (Section 3) - , were included. This allowed for the investigation of whether, according to disaster managers, risk appraisal processes (such as those studied in (Rao et al., 2011)) and coping appraisal processes (such as those studied in (Dang et al., 2014a)) indeed play a role in determining smallholder farmers' intention to adapt to droughts. Simple descriptive statistics were applied to investigate the answers of the disaster managers, so as to evaluate if the top-down view of adaptive behaviour matches with the inquired and observed behaviour of the smallholder farmers, as well as to compare the factors of importance according to the disaster mangers with the components of the existing bounded rational behavioural theories.

### 4.3. Semi-structured smallholder farmer questionnaire design

Additional empirical data about farmer behaviour was collected in a semi-structured questionnaire among 260 smallholder farmers in Kitui East, around different markets along the Kibwezi-Kitui-Kandwia road (Figure 3.2). Cluster sampling and a simple random approach were adopted to gather quantitative data – once a specific neighbourhood was randomly picked, all households in the neighbourhood were contacted for participation. Four trained enumerators, originating from the study area, used the smartphone application KOBO-Toolbox to collect the answers of households willing to participate. A pilot survey of 30 households was conducted to ensure clarity of the questions and to train the enumerators, after which the list of questions was optimized.

The literature overview and the expert feedback from the key informant interviews (4.1) and disaster managers (4.2) were the basis for a household questionnaire designed to validate the use of the Protection Motivation Theory and others for the case study of smallholder farmers in Kitui (see Appendix Table 3B). We adopted the approach suggested by Temessa et al (2019) on testing for the links between drivers and adaptation in three steps: the direct-enquiry method, the direct-ranking method and recording proxies to be used in statistical models (Tessema et al 2019). This resulted in a set of 85 questions verbalising multiple behavioural factors—including people's drought experience, risk perception, susceptibility, coping capacity, self-efficacy, perceived adaptation benefits, perceived adaptation costs, motivation and barriers to adapt, and questions related to the socioeconomic and demographic status of the respondents (descriptive statistics on the socio-economic characteristics of respondents can be found in Appendix table 3C).

The collected data was used to uncover statistical correlations between socioeconomic, behavioural, or cognitive variables and farmers adaptive behaviour (e.g., (Smajgl et al., 2011; Valbuena et al., 2010)) (please find an overview in Appendix table 3D and 3E). We used binary logistic regression techniques to relate these variables to the farmers' intention to adopt new measures in the next season and farmers' past adoption of measures. After doing a Pearson correlation analysis, we performed stepwise logistic regressions and evaluated their goodness of fit based on the Akaike Information Criterion and R-squared values. The Boruta and backward Wald methods were used as stepwise elimination algorithms on the logistic regression, thereby automatically optimising the models (removing correlated and redundant variables, obtaining the best AIC value) (Kursa & Rudnicki, 2010). The p-values and coefficients of the independent variables of the optimised models were used to identify the most critical drivers for adaptive behaviour.

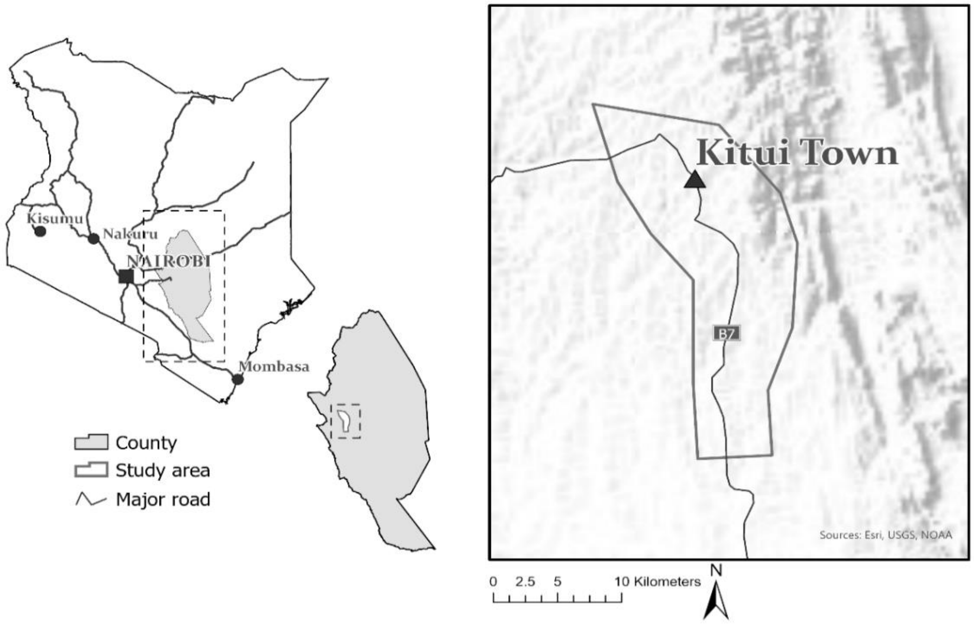


*Figure 3.2: LEFT: Location of study area within Kitui County (centre, grey) in Kenya; RIGHT Kitui town (triangle) and the Kibwezi-Kitui-Kandwia road (B7) along which the survey took place*

### 4.4. Smallholder farmer choice experiment design

In addition to semi-structured survey questions, the 260 smallholder farmers were also asked to participate in a discrete choice experiment (DCE), a stated preference technique used to investigate smallholder farmers' preference towards policy actions, as suggested by (Bateman et al., 2013; Holden, 2015). DCEs are often used to describe the different effects of both attributes of scenarios and characteristics of decision makers on choices they are presented with. Discrete choice analysis, an econometric approach, is often used to evaluate the preference for risk-reducing measures (e.g., (Conrad & Yates, 2018; Schaafsma et al., 2018)). DCE models specify the probability that an individual respondent chooses a certain scenario among a set of alternative scenarios: in this case a specific combination of governmental drought policies. Farmers are assumed to select the scenario that would increase their likelihood of adopting the most. This highest utility scenario is the sum of the utilities of each attribute but is also influenced by the farmers' socioeconomic situation (Train, 2020). The relative importance of the attributes of a DCE provides valuable information for the prediction of future adaptive behaviour under changing policy conditions (Conrad et al., 2017).

The DCE in this research was designed to evaluate the change in farmers' intention to adopt drought adaptation measures, for scenarios with a mix of top-down drought interventions (attributes) that could potentially erase the current barriers to adoption. This list is based on current policies regarding drought adaptation in Kenya, which were also mentioned during the key informant interviews. For example, the Kenya Vision 2030 promotes integrated proactive drought management for dryland farmers through improved extension services and increased access to financial services, such as affordable credit schemes for people in the Arid And Semi-Arid Lands of Kenya (Republic of Kenya, 2013). Besides, building on the Ending Drought Emergencies plan (2013–2017) (Government of Kenya, 2014), the National Drought Management Authority prioritises drought early warning systems, and aims to establish ex-ante cash transfers to upscale drought disaster risk financing (National Drought Management Authority (NDMA), 2015). Also other authors concluded that more resources in terms of credit facilities, access to climate change information, and extension services should be availed to farmers in areas affected by climate change and variability (Mutunga et al., 2017).

*Table 3.4: Choice experiment setup: attributes (governmental actions) in the first column, their possible levels right of it*

| | **Level 0 (business as usual)** | **Level 1** | **Level 2** |
|---|---|---|---|
| ***Extension services*** | Infrequent; access for 15-25% of the households | Access for everyone, Once a year | Access for everyone, every season (Twice a year) |
| ***Early Warning system*** | Not reliable | Yearly outlooks | Seasonal predictions |
| ***Cash transfer*** | Ex-post at best; for less than 40% of the farmers | Ex-ante (lump sum) for all farmers in need | Ex-ante (two sums) for all farmers in need |
| ***Credit schemes*** | Access for only 1.5% rates at >10% | Access to everyone, rates at 5% | Access to everyone, rates at 2% |

Using a DCE (table 3.4) can help identify preferences for governmental policies as well as analyse to what extent drought management policies will steer adaptive behaviour, which explains how effective they are at reducing the farm household drought disaster risk. Respondents were asked to choose eight times between two alternative policy scenarios (a combination of four governmental actions with various combinations of level 1 and 2) and the business-as-usual case (the four governmental actions on level 0) and indicate in which scenario they would most likely adopt a new adaptation measure. The experimental design was controlled random – the actions and their levels on each choice card were balanced and could overlap. Level overlap was allowed to occur, meaning that in a single decision situation an action could have the same level in both options presented (Holm et al., 2016).

Multiple applications of a mixed multinomial logit model, which assumes heterogeneity in preferences for different alternative-specific variables (McFadden & Train, 2000; Train, 2004), were tested to investigate the policy preferences of the 260 farmers. The utility functions of this mixed – also called random parameter – logit model consisted of the linear sum of the attribute values and their weight coefficients, indicating their importance and random variation error terms per attribute (Croissant, 2003a). Using 1000 draws, random parameters with normal distributions were estimated for all attributes, and an error-component was included for the two options versus the opt-out. They showed not only the average preferences of the respondents but also its heterogeneity, indicating a distribution of preferences caused by both observable and unobservable alternative characteristics (Croissant, 2003b). The goodness-of-fit of the models was checked using the AIC test, a measure of the relative quality of statistical models, analysing the trade-off between model complexity and goodness-of-fit for a given set of data.

## 5. Results

### 5.1. Key informant interview outcomes

The concept diagram in Appendix 3B was created by combining Fuzzy Cognitive Maps of all key informant interviews, a bottom-up way of displaying the Kitui context of smallholder drought disaster risk management. Three layers can be distinguished: (1) adaptation measures, signifying the level of vulnerability to drought disaster risk; (2) adoption factors, identifying the drivers for adaptation; and (3) governmental and nongovernmental organisations (NGOs), representing the policy context. Three types of adaptation measures were identified by the respondents: practices related to soil and water conservation (i.e., grey infrastructure and techniques to avoid degradation); climate-smart agriculture (agronomic practices to avoid drought-induced crop loss); and livelihood diversification (directly increasing resilience to shocks). The adoption factors revealed in the Fuzzy cognitive Map can be classified into drivers or barriers related to knowledge, self-efficacy, response efficacy, response costs, attitude, risk perception, and social networks. This means that the Protection Motivation Theory alone is not able to explain all possible drivers for adaptive behaviour mentioned by the key informants, as social network and attitude, two factors covered the Theory Of Planned Behaviour, also appeared on the map. Lastly, key informants perceived that governmental organisations and NGOs can affect all of the acknowledged drivers of/barriers to adoption through direct and indirect policies and actions.

Moreover, from the key informant interviews with example farmers, three additional conclusions could be drawn: (1) Farmer-to-farmer networks spread the knowledge on adaptation strategies (guided by NGOs), thus enhancing the implementation of adaptation measures. Besides, there are pioneer farmers who do not receive extension services but nevertheless want to adopt new structures; however, they lack the knowledge or financial means. (2) When not in poverty, and with knowledge on business and farm financial management (i.e., education), farmers have fewer barriers. However, when trapped in poverty, conditional food and financial aid can help build sustainable livelihoods, creating families that are not dependent on external support anymore. (3) Corruption is a critical factor hindering the implementation of adaptation measures. Large costs are not bearable because of corruption and fluctuating market prices. Interestingly, two of the three key aspects mentioned above – networks, corruption - are not so pronounced or even absent in the Protection Motivation Theory, although one could argue that they indirectly influence the coping appraisal (self-efficacy, coping efficacy, and coping cost). The influence of networks however also strongly relates to the subjective norm factor in the Theory of Planned Behaviour, giving credibility to this latter theory.

### 5.2. Disaster manager survey outcomes

Based on the survey among policymakers and disaster risk reduction officers, the policy makers' perspectives on smallholder drought disaster risk and adaptation could be obtained (figure 3.3). Increasing knowledge was (on average) ranked as the most important motivation to adapt, above expected financial gain (on average 2nd), financial help (on average 3rd) and experienced drought disaster risk (on average 4th). While the effect of neighbours is on average ranked lowest, opinions vary as 26% has ranked this as most important but 34% as least important. Asked about the timing of decisions by smallholder farmers, they were thought to have the highest motivation to adapt right after a drought (52%) or after they receive training (33%), aligned with increasing knowledge (79%) and increasing awareness (71%) being the best strategies for supporting smallholder adoption of adaptation measures. The disaster manager survey further revealed that adaptive behaviour is thought to be bounded by risk perception, response appraisal, and knowledge. These outcomes support the Protection Motivation Theory rather than the Theory of Planned Behaviour as the theory describing smallholder farmer adaptive behaviour under drought disaster risk, but it should be noted that the answers varied significantly among respondents making it challenging to draw hard conclusions. No pattern (e.g., country based differences or local versus national managers) in this heterogeneity of answers could be found either.

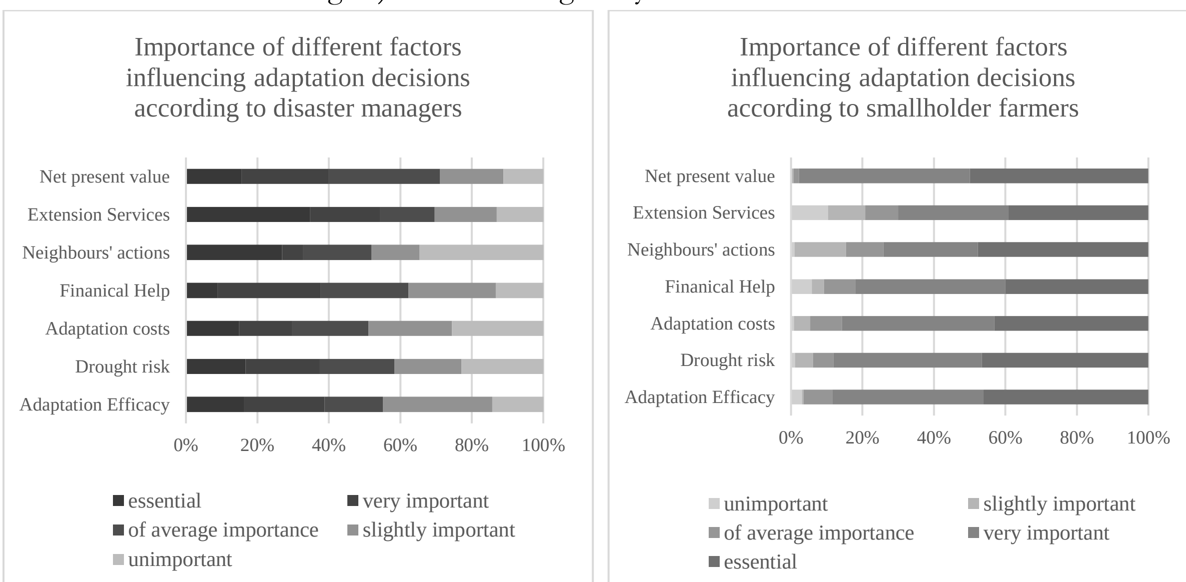


*Figure 3.3: Ranking of importance of different factors influencing the decisions whether or not to adopt by Disaster risk managers (N = 49) (LEFT) and by smallholder farmers (N = 260) (RIGHT).*

### 5.3. Semi-structured smallholder farmer questionnaire outcomes

When farm households were asked about the importance of various factors in their decision whether to adopt new drought adaptation measures (figure 3.3), 50% found the yield gain, net present value, essential to be essential for their adaptive behaviour, whereas 48%, 47%, 46% found social influence (actions of neighbour), experience of multiple crop failures (drought disaster risk), and efficiency in reducing water shortages (adaptation efficacy), to be essential, respectively. Moreover, 43% of the farm households would not install measures if the installation costs were higher, 40% would not if they did not receive financial help and 39% would not if they did not receive extension services. Here, the social norm factor of the Theory of Planned Behaviour seems essential, in contrast to the results of the disaster manager survey, which estimated social influences as less important. However, risk and efficacy, factors in the Protection Motivation Theory, are also seen as critical by almost half of the respondents.

Looking into the barriers (Table 3.5), clearly poverty tops the list in challenges to overcome for the decision to adopt measures. Both money and labour capital stops people from planning to adopt measures even while wanting to do so. Lack of necessary skills is another important barrier, and also a lack knowledge on which measure to install is limiting adoption. Clearly, the (perceived) self-efficacy, a factor in both the Theory of Planned Behaviour and Protection Motivation Theory, matters, next to purely financial constraints present in all theories. Moreover, contrasting the importance of yield gain, net present value of the measures, more than 50% of the farm households never did perform a proper cost–benefit analysis, revealing a split in the respondent pool and refuting the assumptions of perfect information and economic rationality used in e.g., the Expected Utility Theory.

*Table 3.5: Percentage of respondents acknowledging to have experienced the limiting factor in question. Table showcases (left) the barriers to adopting new adaptation measures (based on future adoption behaviour): challenges foreseen by those who plan to adopt new measures soon (N=106) and (right) the hurdles for those who wish to but are not able to plan to adopt new measures (N=147). 6 Households indicated they had no intention to have more measures, and thus were not asked either of these questions.*

| **Barriers for adoption of adaptation measures** | **% of those who plan to adopt** | **% of those who wish but not plan** |
|---|---|---|
| *Limited access to credit markets* | 42% | 20% |
| *Limited skills to implement measures* | 48% | 24% |
| *Lack of a suitable location for the measures* | 20% | 16% |
| *Lack of labour to install the measures* | 51% | 35% |
| *Limited financial capacity to adopt the measures* | 86% | 83% |
| *Limited access to input materials* | 35% | |
| *No knowledge on effective measures* | | 31% |

A logistic regression analysis (Table 3.6, accuracy 83%) evaluating the factors present in existing theory related to having adaptation measures, revealed that people who have adopted measures in the past have experienced less drought events. This is possibly a result of being more resilient to drought disasters after adapting to them, rather than a driver at the time of making the decision. However, risk perception (a factor in the Protection Motivation Theory) clearly plays a role: people who experience frequent seasons with water scarcity, and/or those who fear such seasons, and/or those who are afraid of climate change, were more likely to have adopted measures. Furthermore, farm households with larger land had a 65% higher likelihood of having adopted measures, a factor that can indicate the potential gain of adaptation – assuming the drought-induced losses have a bigger influence on the livelihoods of households with more land. Also household heads who attended extension services were almost three times more likely to have adopted measures in the past. Hence, access to knowledge, a factor also apparent in the Fuzzy Cognitive Map, indicated by the disaster managers and strongly linked to perceived self-efficacy (a factor of both the Protection Motivation Theory and Theory of Planned Behaviour), is an important driver for adaptation. Interestingly, farm households who trust forecasts were less likely to have adopted, maybe because they rely on preparedness rather than long-term adaptation.

*Table 3.6: Binary logistic regression with "having adopted adaptation measures" as dependent variable. Model selection was based on maximizing overall fit for main effects with an estimated AIC of 215. Odds ratio and interval of odds ratios are shown. Significance levels: p<0.1 . ; p<0.05 *; p<0.01 **; p<0.001 ***.*

| Drivers PAST behaviour | ODDS Ratio | | 2.50% | 97.50% | Link with theory |
|---|---|---|---|---|---|
| (Intercept) | 0.58 | | 0.16 | 2.13 | |
| Experience seasons with water scarcity | 1.18 | . | 0.99 | 1.41 | Risk perception |
| Scared of climate change | 1.41 | . | 0.97 | 2.06 | Risk perception |
| Fear from droughts and water shortage | 2.07 | *** | 1.55 | 2.83 | Risk perception |
| Number of drought disasters experienced | 0.84 | ** | 0.75 | 0.93 | *unclear* |
| Trust in forecasts | 0.72 | . | 0.48 | 1.06 | *unclear* |
| Access to forecasts | 0.71 | | 0.45 | 1.11 | Knowledge |
| Attended extension service trainings | 2.97 | ** | 1.33 | 6.96 | Knowledge |
| Access to group credit scheme | 1.82E8 | | | | Financial strength |
| Recipient of farm subsidies | 1.54E9 | | | | Financial strength |
| Size of own land | 1.65 | *** | 1.27 | 2.24 | Financial strength |

*Table 3.7: Multinomial Poisson regression with "number of adopted adaptation measures" as dependent variable. Model selection was based on maximizing overall fit for main effects with an estimated AIC of 757. Odds ratio and interval of odds ratios are shown. Significance levels: p<0.1 . ; p<0.05 *; p<0.01 **; p<0.001 ***.*

| Drivers PAST behaviour | ODDS Ratio | | 2.50% | 97.50% | Link with theory |
|---|---|---|---|---|---|
| (Intercept) | 0.69 | | 0.44 | 1.08 | |
| Perceived vulnerability | 0.83 | *** | 0.74 | 0.93 | Risk perception |
| Fear from droughts and water shortage | 1.23 | *** | 1.11 | 1.37 | Risk perception |
| Trust in forecast | 0.84 | *** | 0.76 | 0.93 | *unclear* |
| Member of a farm group | 1.38 | ** | 1.11 | 1.70 | Knowledge |
| Performed a cost-benefit analysis | 1.41 | ** | 1.15 | 1.74 | Knowledge |
| Size of own land | 1.05 | *** | 1.03 | 1.08 | Financial strength |
| Age of household head | 1.01 | . | 1.00 | 1.02 | Self-efficacy |
| Amount of household members | 1.06 | * | 1.00 | 1.12 | Self-efficacy |

*Table 3.8: Binary logistic regression with "planning to adopt new measures" as dependent variable. Model selection was based on maximizing overall fit for main effects with an estimated AIC of 280. Odds ratio and interval of odds ratios are shown. Significance levels: p<0.1 . ;p<0.05 *; p<0.01 **; p<0.001 ***.*

| Drivers FUTURE behaviour | Odds Ratio | | 2.5% | 97.5% | Link with theory |
|---|---|---|---|---|---|
| (Intercept) | 0.22 | | 0.06 | 0.75 | |
| Usefulness of Extension Services | 0.47 | . | 0.20 | 1.09 | *unclear* |
| Faith in god as saviour | 0.42 | *** | 0.26 | 0.64 | Self-efficacy |
| Household size | 1.12 | . | 1.00 | 1.28 | Self-efficacy |
| Influence of adaptation neighbours | 1.42 | | 0.92 | 2.21 | Social norm |
| Number of adopted measures | 1.44 | ** | 1.12 | 1.86 | Self-effic. / knowl. |
| Access to forecasts | 1.64 | * | 1.11 | 2.45 | Knowledge |
| Trust in forecasts | 0.71 | . | 0.49 | 1.00 | *unclear* |
| Perceived efficiency of the measures | 1.77 | ** | 1.17 | 2.77 | Adaptation efficacy |
| Access to group credit scheme | 6.90 | | 0.81 | 152.06 | Financial strength |
| Access to individual credit scheme | 3.30 | . | 0.95 | 13.74 | Financial strength |
| Performed a cost-benefit analysis | 1.91 | . | 0.99 | 3.71 | Financial strength |
| Total farm expenses | 1.00 | | 1.00 | 1.00 | Financial strength |

When analysing the multilinear relationship between behavioural factors present in existing theory and the number of drought adaptation measures adopted (Table 3.7), risk perception and knowledge appeared to be relevant again: fear of droughts and water shortage and the ability to perform a cost–benefit analysis were positively related to the number of measures. The model (accuracy of 78%) showed that older people (having experienced more drought years) and larger households (more labour power), are positively linked to having more measures: both can be linked to the perception of self-efficacy. Also people with a larger farm size (more benefits/ larger financial consequence of drought-induced production loss) have a higher odds. Again, farm households with less trust in forecasts appeared to have adopted more measures, supporting the notion that forecasts (trust) move people from relying on preparedness to investing in adaptation. Elements from the Expected Utility Theory (cost–benefit rationale), and Protection Motivation Theory (perceived capacity, perceived risk) were visible, but not one theory was able to contextualise all regression results.

When statistically analysing potential future actions – namely predicting farmers' plans to adopt new adaptation measures (Table 3.8, accuracy of 78%) – it was clear that having adopted multiple measures before, having a larger household, having performed a cost–benefit analysis, and having a positive attitude toward the efficiency of these measures increased the likelihood of planning for new measures by 44%, 12%, 91%, and 77%, respectively. These factors are related to the perceived self-efficacy and perceived adaptation efficacy of the Protection Motivation Theory. Understandably, the belief that god is the only one that can protect households from disasters – decreasing self-efficacy – reduced the intention to adopt. On the other hand, having access to credit made farm households three times as likely to plan for new adaptation measures, possibly because this reduces initial investment costs. While having access to forecasts seemed to increase adaptation intention by 65%, trust in forecasts again appeared to negatively incentivise people to adopt new measures in the same analysis. Surprisingly, finding extension service training less useful increases the likelihood of planning for new measures: maybe the lack of extension support related to agronomic practices steers them to into making permanent adaptation decisions, but there may as well be another explanation for this.

### 5.4. Smallholder farmer choice experiment outcomes

In a first analysis evaluating discrete choices (Table 3.9), results indicated that, as expected from the key informant interviews and disaster manager survey, receiving more and better tailored extension services, having an improved early warning system, receiving ex-ante cash transfers, and having easier access to low-rate credit schemes - none of which were the case in the current situation (business-as-usual) - all increase farmers' intention to adopt new drought adaptation measures. Clearly, overcoming the barriers of access to credit, trust in forecasts, and relevance of training – as was evident from the previous regression analyses – can indeed increase farm households' intention to adopt. If people received extension services about innovative adaptation measures, they would be 51% more likely to adapt; if they received timely and trustworthy early warning systems, they would be 54% more likely to adapt; and if they received ex-ante cash transfers, they would be 11% more likely to adapt. The attribute credit was negative as lower interest schemes were preferred: per unit increase in the interest rate, their likelihood to adopt decreased by 7%.

Significant standard deviations existed in the random parameters, revealing considerable heterogeneity. The standard deviations for all attributes, except early warning, were larger than the means of the random parameters: there was a sign-switch within the sample meaning some respondents assigning positive utility changes to an attributes, while others expressed negative utility change – showing substantial heterogeneity in the preferences. However, in general, the opt-out rate was low, with only 21% of choices for the business-as-usual scenario. The main motivation for choosing for this scenario was that respondents already planned to adopt new measures, and thus, governmental drought management policies would not increase their intention to adopt. It is thus not surprising that the business-as-usual situation (alternative-specific constant) had a large negative effect size and was significant, reflecting a general interest in change and dissatisfaction with the current situation – as was also clear from the survey where more than 80% indicated that the government should be responsible for increasing farm resilience to drought. There was also a large significant standard deviation, demonstrating heterogeneity towards business as usual, but there was no immediate switch in sign.

*Table 3.9: Random parameter logit model of the discrete choice experiment. Log-Likelihood: -1497. Odds ratio and interval of odds ration are shown. Significance levels: p<0.05 *; p<0.01 **; p<0.001 ****

| Attributes | Odds Ratio | | 2.5% | 97.5% |
|---|---|---|---|---|
| Extra extension services | 1.51 | *** | 1.38 | 1.65 |
| Better early warning system | 1.54 | *** | 1.33 | 1.69 |
| Ex-ante cash transfers | 1.11 | * | 1.03 | 1.20 |
| Low-rate credit schemes | 0.93 | *** | 0.91 | 0.95 |
| Business-as-usual | 0.01 | *** | 0.003 | 0.03 |
| standard deviation extension service | | *** | | |
| standard deviation early warning | | * | | |
| standard deviation cash transfer | | *** | | |
| standard deviation credit scheme | | *** | | |
| standard deviation business-as-usual | | *** | | |

By evaluating discrete choices that allow for mixed interaction effects between scenario attributes themselves (Appendix Table 3F) and socioeconomic farm household characteristics (Appendix Table 3G, left) or cognitive–behavioural factors and perceptions (Appendix Table 3G, right) , it is evident that multiple factors influenced preferences for the four investigated attributes. Indeed, a preference for more extension services went hand in hand with one for ex-ante transfers and good credit schemes, and also transfers and credit schemes concurred. A preference for early warning systems did not quadrate with one for extension services or ex-ante transfers. The following two paragraphs try to scrutinize the underlying reasons why these preferences are heterogeneous and correlated.

Firstly (Appendix Table 3G, left), households with more measures preferred extra extension services, better early warning systems, and ex-ante cash transfers more than average, and increased the effect of lower-rate credit schemes on adaptation intention. Possibly, the need for tailored extension services (training) and ex-ante cash transfers (financial aid) to maintain already adopted measures when a drought early warning is sent out, can improve the effect of these measures in mitigating the drought impact. Factors such as age, education level, and already attending extension training decreased the effect of providing extra extension services on the intention to adapt: more experienced farmers did not prefer policies related to additional training. The effect of better early warning systems was lower for more educated households and those who were members of a farm group, probably because they have other means of accessing up-to-date climate and weather data. Education level, attending extension training, and a larger off-farm income decreased the effect of credit policies; logically wealthy households do not need such a policy. Being a member of a group strengthened the effect of credit policies, probably because of the existence of group credit schemes, and also those with more land did prefer low-rate credit schemes. Clearly – but not surprisingly, a differentiated "business-as-usual" or baseline regarding knowledge and finances strongly influences the effect of the four policies on the intention to adopt new adaptation measures.

Secondly (Appendix Table 3G, right), factors such as "being influenced by actions of neighbours (social norms)", "having experienced more droughts (risk appraisal)", and "having access to enough information (self-efficacy)" decreased the positive effect of extension services on the intention to adapt. However, these factors had a positive interaction effect with credit schemes: having access to enough information increases the effect of credit schemes on the intention to adapt; making this governmental action more successful in increasing uptake of measures among well-informed farm households. Total income (cost perception) had negative interactions with both extension services and early warning systems. Furthermore, perceiving that once has the capacity to cope (self-efficacy) had a positive interaction with early warning systems. Moreover, performing a cost–benefit analysis (behaving economically rational such as assumed in the Expected Utility Theory) and having large adaptation spending (adaptation appraisal) had positive interactions while being influenced by neighbours (social norm) had a negative interaction with ex-ante cash transfers. Clearly, the factors of the socio-cognitive theories influence the effect of governmental policies.

# 6. Discussion

## 6.1. Adaptive behaviour of smallholder farmers in Kitui

By analysing interviews with key informants, the answers of the disaster risk managers and the results from the smallholder farmer survey, we revealed that i.a. experience with water scarcity, perception of climate change, fears from drought and water shortage, as well as attendance to trainings, faith in god, access to and faith in forecasts, the number of previously adopted measures, size of farm land, perceived efficiency of measures, access to credit, total expenses and performing a cost-benefit analysis explain past and future adaptive behaviour. Comparing answers from disaster managers and smallholder farmers, the former seem to overestimate the effect of extension while underestimating the effect of gains: while extension services indeed explain past behaviour in the regression analysis- usefulness of extension services seemed to limit the intention to adapt in the future. Summarizing all these findings, we can identify five main outcomes:

First of all, both adaptation costs and adaptation efficacy (linked amongst others with field size) are of uttermost importance, as financial strength is the most-mentioned barrier – similar to (Drechsel et al., 2005; Gbegbelegbe et al., 2018a; Ifejika Speranza, 2010; Kasyoka Nthenge, 2016; Khisa1 et al., 2014; Muhammad et al., 2010a; Nkatha, 2017; Okumu, 2013b; Owuor et al., 2005; Shikuku et al., 2017; Tongruksawattana & Wainaina, 2019) and others – and yield gain the most important motivator for decisions of the smallholder farmers in this case study. The fact that farmers able to perform a cost-benefit-analysis have a higher likelihood of adoption further strengthens this evidence, which is also found in (Drechsel et al., 2005; Muhammad et al., 2010a; Mwangi et al., 2015; Nkatha, 2017). While considering costs and benefits hints to utility maximizing behaviour (Expected Utility Theory), it is also on the basis of the Theory of Planned Behaviour (Sutton, 2001) and is in a less direct way present in the Protection Motivation Theory where coping appraisal is influenced by the response costs of action and the perceived response efficacy (Maddux & Rogers, 1983).

Secondly, our multi-method analysis proves the significance of knowledge as driver for adaptation decisions in this case study. Attendance to trainings, farmer networks and access to forecasts, can be all classified under human capital. This human capital factor, leading to a perceived own ability to respond, is found to determine the adoption of farm-level adaptation measures in preceding studies (e.g. (Adimo et al., 2012; Bedeke et al., 2019; Bryan et al., 2019, 2013d; Deressa et al., 2009; Gbetibouo, 2009; Kurukulasuriya et al., 2006; Muhammad et al., 2010a)) and can be seen as a proxy for perceived self-efficacy. Also mistrust in forecasts (from the questionnaire), corruption (from the interviews), belief in god as saviour (from both) and the influence of already adopted measures (from the DCE) can be related to this self-efficacy factor, although not much existing research literally mention these proxies. Self-efficacy, the perception of how well one is able to cope with a situation based on their skills and circumstances, is an essential factor to describe the decision making process in both the Protection Motivation Theory and the Theory of Planned Behaviour (Gebrehiwot & van der Veen, 2015; Keshavarz & Karami, 2016c; Le Dang et al., 2014; Niles et al., 2016).

Thirdly, social networks (i.e., farm groups) were mentioned in the interviews (also in (Bedeke et al., 2019; van Duinen et al., 2012)) but appeared not to be significant in the statistical analyses and showed a lessening effect on the influence of governmental actions. They clearly influence adaptation decisions, but this can be through knowledge distribution - influencing the self-efficacy factor, or through inflicting normative believes, the subjective norm factor in the Theory of Planned Behaviour. Fourthly, the importance of (a subjective) drought disaster risk as driver for adaptation decisions is apparent in this case study, through perceived vulnerability, experience with and fear of droughts and water scarcity, and perception of climate change. This risk-appraisal factor is found to motivate adoption of farm-level drought adaptation measures in preceding studies (e.g. (Deressa et al., 2011; Di Falco, 2014b; Ochieng et al., 2016; Regasa & Akirso, 2019b; Tripathi & Mishra, 2017); but not found in (Carlton et al., 2016) and varying results in (Tessema et al., 2019)). Threat appraisal is an important factor in the Protection Motivation Theory, which states that people have to perceive a certain level of risk before they will consider acting (REF).

Finally, assessing the effect of policy measures related to extension services, early warning systems, ex-ante cash transfers, and credit schemes, we evidence that all would have a positive influence on adaptation intention, thus encouraging adaptation decisions; a similar positive link was found in (E. Bryan et al., 2009; Ochieng et al., 2016; Tessema et al., 2019) (credit); (Gbetibouo, 2009; Kurukulasuriya et al., 2006) (extension services), (Evelyn & Charles, 2018; Silvestri et al., 2012b) (early warning), (E. Bryan et al., 2013e; Silvestri et al., 2012b)(aid). However, the effect was found to be highly heterogeneous: Farm households who were already able to adopt certain measures generally had a higher preference for the policies, and household heads with higher education levels generally had a lower preference; however, the opposite was true for low-rate credit schemes. The effect of neighbours or farm groups decreased the positive effects, showing the capacity of social networks to complement the need for governmental action.

Clearly, even with the strong presence of financial factors in the decision-making process of smallholder farmers in Kitui, this Chapter shows that the assumption of purely economic rational behaviour should be avoided. From the more complex behavioural theories, most of the factors with significant influence in this case study can be linked to factors of the Protection Motivation Theory (such as in (Dang et al., 2014b; Grothmann & Patt, 2005; Keshavarz & Karami, 2016d; Regasa & Akirso, 2019b; van Duinen et al., 2016) and others), while there is less evidence for the other theories. For multiple variables, it remains unclear whether they can be seen as a proxy for a factor in one of the decision-making theories, which complicates validating the use of a specific theory in this case study. Moreover, the heterogeneity in and correlation between policy references are not apparent in most behavioural theories, which in general assume that people behave more or less in the same way, while this case study evidences the opposite. Notwithstanding, it is evident that if adaptive behaviour is to be included in dynamic drought disaster risk models, in addition to the costs and benefits, the perceived self-reliance, the perceived risk, the social network and the knowledge must also be considered.

### 6.2. Future modelling applications

The information presented in this manuscript – combining theories and empirics- brings insight in the complexities of the adaptive behaviour of smallholder farmers in Kitui. It can be useful for both scientific and decision maker audiences as it can help improve the vulnerability and adaptation dynamics in drought disaster risk models and it can thus both directly and indirectly support the design drought disaster risk reducing policies that are effective and efficient. Our findings could be used to create a theoretical agent-based drought disaster risk model with simple rules depicting the adaptive behaviour of smallholder farm households in semi-arid Kenya (following the framework suggested in Chapter 2) and also provide quantitative evidence of the factors shaping adaptive behaviour, which can be used to calibrate the decision rules of ABMs. Besides, they could be used to structure a system dynamics model (Gies et al., 2014) depicting the socio-hydrological reality of smallholder farmers under drought disaster risk. Such models can deepen the understanding of the intertwined nature of the human and hydrological systems as well as the role of drought disaster risk perception therein. Moreover, DCE allow to explore future adaptation decisions under a changing policy context, providing input for predictive models capable of simulating the effect of policies on future drought disaster risk.

### 6.3. Methodological considerations

The mixed-methods data collection presented in this Chapter was based on both empirical evidence from other studies as well as behavioural theories, thereby overcoming the limitations of both. The participatory cognitive mapping exercise allowed to address the drought disaster risk perceptions of the key informants and improved our understanding of the decision making of smallholder farm households in the semi-arid-Kenyan context. The interviews with the disaster managers provided a top-down view on current drought management practices and policies. As such, the methods can be seen as complementary to study adaptive behaviour and assure both views are included in the design of a detailed household survey with smallholder farm households.

Ideally a multi-year survey would have been set up to evaluate the adaptation decisions of smallholder farmers over time in relation to socio-economic, environmental and policy changes. In our study, this was not feasible so as a proxy, both smallholder farmers' past adaptation decisions and their intention to adopt were evaluated. While doing the former, it is hard to extract the drivers and barriers that existed at the point of decision – as they might have changed over time-, the latter is based on self-reported plans to invest in measures, which might deviate from reality. While both are not ideal, evaluating past behaviour is a method frequently applied in adoption studies and evaluating the intention to adapt is also relevant as this might even better reflect the behavioural drivers for decision (Bryan et al., 2019). Besides, the sampling method might have a bias to farmers with relatively good access to the market, which might not be a ful representation of the diversity of farm household sin the region.

Further, the unconventional application of discrete choice experiments in this Chapter does not investigate a willingness to pay for policies. Rather, we investigated preferences for policies and the potential of policies influencing the respondent's intention to adapt, a technique also applied in other fields (Blaauw et al., 2010; Pechey et al., 2014; Ryffel et al., 2014). This application can be seen as complementary to the logistic regressions linking drivers, barriers and past or intended actions, as this method is able to link factors, smallholder farmer characteristics, not directly to adaptation actions but to preferences for support concerning these adaptation actions.

## 7. Conclusion

In this Chapter, interviews with key informants and a disaster manager survey, complemented by scientific literature on the application of sustainable drought management practices, were used to identify the factors influencing the adaptive behaviour of smallholders at risk of drought. The significance of these factors was tested using data from an extensive survey of small farming families, including a questionnaire and a choice experiment. We compared the empirically discovered drivers and barriers to adaptation with components of existing behavioural theories, and found that risk perception, social networks and knowledge, in addition to adaptation costs and benefits, are essential for drought adaptation decisions among smallholders in Kitui, semi-arid Kenya. In addition, we found that there is significant heterogeneity in the adaptive behaviour of smallholders, which also translates into the heterogeneous - although moderately positive - effect of different government policies, such as relevant extension services, reliable early warning systems, reduced credit rates or cash transfers .

This research supports the conclusion of a variety or research that has suggested the presence of adoption restrictions (such as access to training or financial markets) that hinder the implementation of drought adaptation. Clearly, the assumption of economic rationality and perfect information in the Expected Utility Theory is not sufficient to explain perceived adaptive behaviour. The drivers and barriers that appeared to influence behaviour in this case study have been linked to components of more complex cognitive theories such as the Protection Motivation Theory and Theory of Planned Behaviour: multiple factors, which have been found to be significantly related to past adaptation decisions or adaptation intentions, can be seen as proxies for threat appraisal, self-efficacy and social norms. However, for our case study, no theory could fully describe the observed adaptive behaviour.

Nevertheless, the applied theories were useful in explaining the causal relationships between different socioeconomic and cognitive factors and the eventual adaptive behaviour. The findings help unravel the processes behind smallholder farmer adoption decisions in Kitui and evaluate the impact of four drought policies in this region, while the method showed promise for evaluating the complexity of drought adaptation behaviour, including outside semi-arid Kenya or a smallholder context. Both can be used to identify the most vulnerable groups and developing well-targeted adaptation policies, and to design, calibrate, and validate utility functions to model heterogeneous individual adaptation decisions in dynamic drought disaster risk models.

# Appendix Chapter 3

*Table 3A: Key informants: Both the name of the company/organisation and the function of persons interviewed are mentioned in the first column, the second column contains some background information about the company/organisation.*

| Key informant | Explanation |
|---|---|
| ***ACRE (an Agricultural Climate data analysis and a Business analyst, impact assessment expert)*** | ACRE Kenya, an agriculture and climate risk enterprise, focuses on the whole production chain, adopting a multi-risk approach. They work on irrigation adoption over insurance development (IBLI project, reduced premiums for good practices) to improve access to markets and finance, by surveying and monitoring the production risk (actual and perceived) for farmers. Their current focus is on planting date info and suggestions for crop type, as this is proven to highly influence crop yield. |
| ***SASOL NGO (head of SASOL and technical advisor)*** | Sasol supports local farmers with sustainable agricultural solutions, i.e., water allocation, restocking, providing tools and knowledge. Sasol is the main receiver of an EU funded project on ending drought emergencies (focussing on recovery). While the governmental extension services are based on supply and demand regarding crop production, SASOL focusses mostly on improving and stabilising food supply in order to provide sustainable livelihoods for the impoverished local small-scale farmers. |
| ***Nyumbani Village (Orphanage director)*** | The orphanage is a perfect example of a self-subsistence community, but a lot of foreign money was needed to establish this resilient environment. They implemented a plethora of sustainable land management practices, adopting both soil and water conservation measures and climate-smart agricultural practices. The community is autarkic, and they have projects on improving the water and food security and financial stability of the organisation. |
| ***Ministry of Agriculture, Livestock and Fishing (Director of Water and a water technologist)*** | The department we speak focusses on farmer food security through water supply services. Most priority extension services that they offer concern financial management, investments and on system diagnosis (e.g., Pump failure). Besides, they are responsible for the installation of community water harvesting structures like sand dams, bore holes, drink water tanks, wastewater management and river conservation. |
| ***Kitui Enterprise Promotion Company on Mango farming (Mango cooperative board member)*** | Before it was an enterprise, the mango cooperative (producing mango, mango juice and mango flour, managed from central Kitui by a committee) was a project outcome of an NGO but then value addition became possible and stable, so a business case was developed. Now it is a company owned for 70% by the farmers, providing stable income for more than 1150 farmers (mostly woman). The participant have a role in the management of the enterprise. |
| ***5 first generation students from South-eastern Kenyan University*** | Students (BSc Hydrology and Water Resource Management) from different parts of Kenya: West Kenya, Lake Nailot, Turkana, Plain Nailot, close to Tanzania, Turkana, Plain Nailot, Coast, Malingi, Turkana, Plain Nailot with parents occupied in (agro-)pastoral livelihood activities. |
| ***5 different example farmers, introduced by SASOL foundation.*** | All visited farmers have 'show farms' where other farmers can go to have a look and learn. We asked them how they try to convince others to adopt beneficial adaptation measures and what the largest limitations were for other farmers. Further, we asked their opinion on why other farmers are or are not as successful in implementing climate-smart agriculture, and how government / NGOs could improve to assure climate-smart agriculture in the region |

*Table 3B: Survey questions related to PROTECTION MOTIVATION THEORY (RA: risk appraisal; SE: self-efficacy; AE: adaptation efficacy; AC: adaptation costs) and THEORY OF PLANNED BEHAVIOUR (SN: subjective norm; AT: attitude; SE: behavioural control) and their rationale.*

| Variable | Theory | Question | Rationale |
|---|---|---|---|
| ***Experienced Impact*** | RA | When a drought hit, how severe were the impacts on your farming activities? | 5-Likert-scale question from ‘not severe’ (I didn’t feel an impact) to ‘very severe’(I lost a lot of my crops) |
| ***Attitude to risk*** | RA | I am very scared about droughts affecting my crop production. I want to do anything to protect my farm from water shortage | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Future risk perception 1*** | RA | How likely do you think it is that a severe drought in the next five years will have a negative impact on your farming activities? | 5-Likert-scale question from ‘it is impossible to happen’ to ‘it will certainly happen’ |
| ***Future risk perception 2*** | RA | How do you think, in future, the amount of water available to you will change if there are no additional water harvesting systems build | 5-Likert-scale question from ‘there will be way less water available’ to ‘there will be a lot more water available’ |
| ***Relative vulnerability*** | RA | If you compare the situation of your family situation to the rest of the community, do droughts affect you...? | 5-Likert-scale question from ‘a lot less than other households in my community’ to ‘much more than other households in my community’ |
| ***Perceived vulnerability*** | RA | I am very vulnerable to drought disaster risks. I suffer a lot from the possible impacts | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Perceived self-efficacy*** | SE | I do believe that I am able to avoid the consequences of droughts in my household. I do have control over the expected drought impacts | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Faith*** | SE | I do believe that only God can protect my household against droughts. Everything is decided by fate | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Risk information 1*** | SE | I do receive enough forecasts and early warnings in face of droughts | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Risk information 2*** | SE | The forecasts and drought warnings I receiver are trustworthy; I can use them to adjust my farm practices | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Risk appraisal 1*** | RA | If the risk on drought and water shortage was lower, I would not have adopted these agricultural water management measures | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Risk appraisal 2*** | RA | How important is "having had a lot of water shortages for my crop production" for your decision to install new drought adaptation measures? | 5-Likert-scale question from ‘not important at all (I would install it anyway)’ to ‘absolutely essential’ |
| ***Perceived efficiency*** | AE / AT | I think drought adaptation measures such as zai pits, ponds or extra watering through irrigation are effective in reducing drought impact" | 5-Likert-scale question from ‘strongly disagree’ to ‘strongly agree’ |
| ***Importance costs*** | AC | How important is "the cost of installation and maintenance" for your decision to install new drought adaptation measures? | 5-Likert-scale question from ‘not important at all (I would install it anyway)’ to ‘absolutely essential (I would not install it if the costs were very high)’ |

| | | | |
|---|---|---|---|
| ***Importance benefit*** | AE | How important is "the expected yield gain" for your decision to install new drought adaptation measures? | 5-Likert-scale question from 'not important at all (I would install it anyway)' to 'absolutely essential (I would not install it if there was no yield gain)' |
| ***Importance financial aid*** | AC | How important was getting financial help for your decision to install new drought adaptation measures? | 5-Likert-scale question from 'not important at all (I would install it anyway)' to 'absolutely essential (I would not install it if there was no support)' |
| ***Adaptation information*** | SE | I do receive enough information about drought adaptation measures options for agriculture | 5-Likert-scale question from 'strongly disagree' to 'strongly agree' |
| ***Importance information*** | SE | How important is it to get information from an NGO or Governmental extension workers / trainings about drought adaptation measures for your decision to install new measures? | 5-Likert-scale question from 'not important at all (I would install it anyway)' to 'absolutely essential (I would not install it if there was no information)' |
| ***Importance social network*** | SN | How important are/were the drought adaptation measures choices of your neighbours or farmers in your network for your decision to install new water harvesting measures? | 5-Likert-scale question from 'not important at all (I would install it anyway)' to 'absolutely essential (I would not install it if nobody recommended it)' |

*Table 3C: Descriptive statistics of the 260 farm households in the semi-structured questionnaire and the discrete choice experiment*

| CHARACTERISTICS | VALUE |
|---|---|
| **Age of respondent** | 42 |
| **Gender of respondent (female)** | 63% |
| **Illiterate respondent** | 4.6% |
| **Able to perform a proper cost benefit analysis** | 52% |
| **Household size** | 5.9 |
| **Farmer network size** | 18 |
| **Farm size** | 1.25 ha |
| **Farm under maize** | 0.71ha |
| **Producing maize** | 97% |
| **Earning less than 1000 USD per year** | 37% |
| **Earning more than 400 USD per year** | 33% |
| **Installed a drought adaptation measures** | 77% |

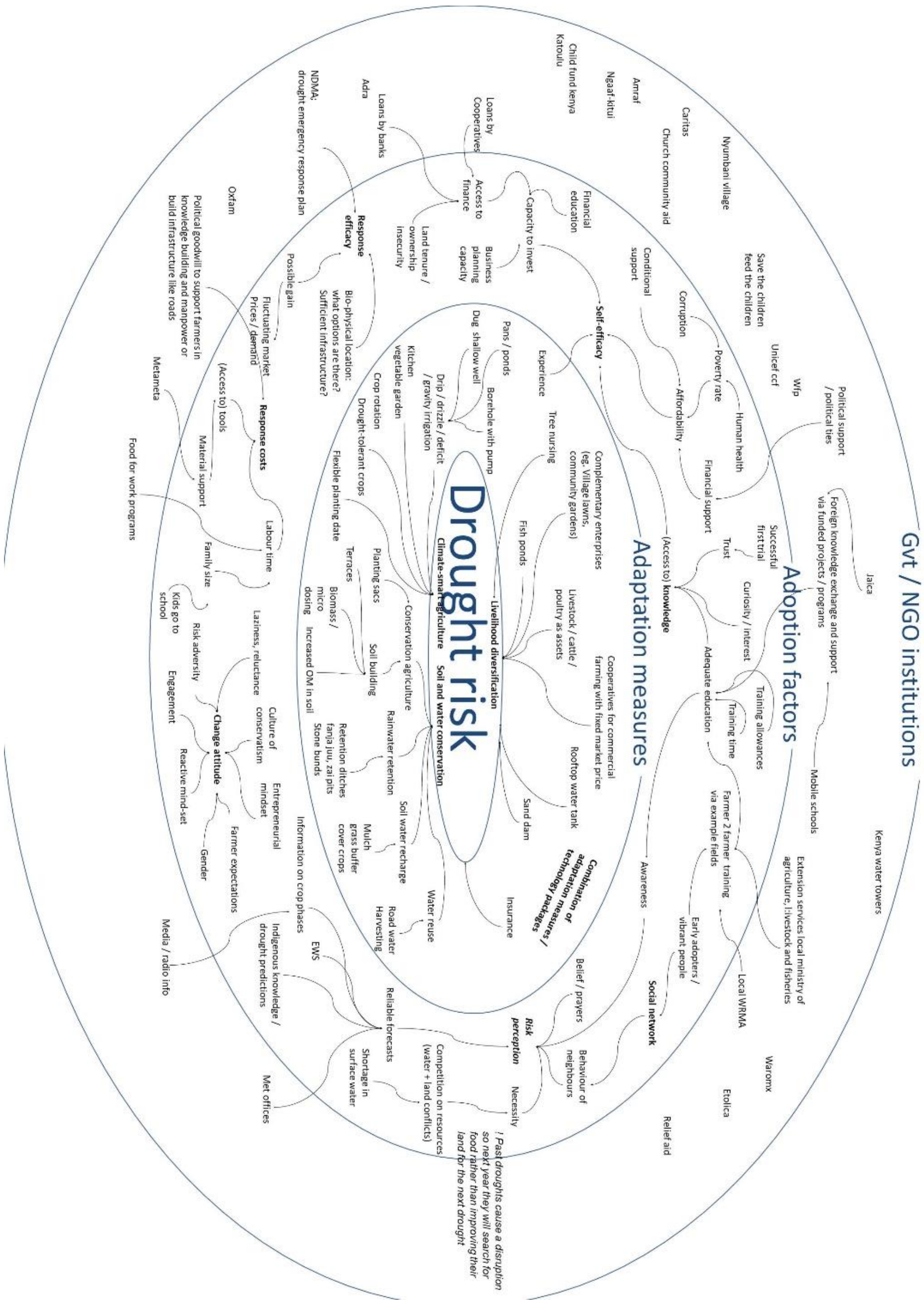


*Figure 3A: Mapping the drought disaster risk context in Kitui based on key informant interviews with scholars, first-generation students, local authorities and NGOs, and pioneer farmers. This fuzzy cognitive map (FUZZY COGNITIVE MAP) served as guidance on further questionnaire development to be able to simulate the situation in Kitui in more detail.*

*Table 3D: Correlation coefficients (R values) for all variables that have a p<0.001 significant relation with the variable on top of the columns.*

| **access to forecast** | | **Perceived capacity** | | **number of droughts experienced** | | **Intention to adopt new measures** | | **No. measures adopted** | | **Attending trainings** | | **Sufficient information** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| access to information | 0.66 | Total expenses | 0.53 | importance of efficiency | 0.60 | Importance of the outcome of a CBA | 0.31 | size of the farmland | 0.39 | useful trainings | 0.51 | forecast | 0.66 |
| thrust in forecasts | 0.65 | Food expenditures | 0.51 | Importance risk | 0.60 | Able to perform a CBA | 0.27 | Importance of neighbours' decisions | 0.3 | Effect of neighbours | 0.44 | useful trainings | 0.62 |
| useful trainings | 0.57 | Expenditures off-farm | 0.38 | importance of costs | 0.56 | Amount of droughts experienced | 0.26 | influence of risk perception | 0.25 | Member group | 0.38 | importance of trainings | 0.60 |
| importance of trainings | 0.54 | Farm expenses | 0.34 | Importance of fin. aid | 0.44 | Perceived efficiency of existing measures | 0.27 | farm expenses | 0.24 | importance of CBA | 0.33 | thrust in forecasts | 0.55 |
| Importance of fin. aid | 0.42 | Expenditures farm | 0.34 | importance of CBA | 0.36 | Importance of adaptation efficacy | 0.25 | getting financial help in terms of a gift | 0.21 | Drought years | 0.32 | Importance of fin. aid | 0.49 |
| importance of costs | 0.41 | Climate change fear | 0.33 | access to information | 0.34 | Effect of neighbours | 0.23 | being able to perform a CBA | 0.21 | CBA | 0.31 | importance of costs | 0.47 |
| Limited Skills | 0.35 | importance of actions neighbours | 0.30 | Effect neighbours | 0.34 | Importance of risk perception | 0.25 | Importance of financial help | -0.21 | Lack Labour | 0.30 | perceived efficiency | 0.42 |
| perceived efficiency | 0.34 | Adaptation spending | 0.28 | useful trainings | 0.33 | access to information | 0.21 | Importance of extension services | -0.23 | access to information | 0.28 | importance of CBA | 0.38 |
| Perceived frequency | 0.34 | Seasons spend in water shortage | 0.26 | Attendance to trainings | 0.32 | faith in god | -0.29 | Having access to forecast | -0.26 | importance of trainings | 0.28 | Importance risk | 0.38 |
| importance of risk | 0.32 | Measures adopted | 0.23 | Disaster fear | 0.31 | | | Feeling vulnerable to droughts | -0.3 | importance of risk | 0.28 | Limited Skills | 0.36 |
| importance of efficiency | 0.30 | No financial help | 0.22 | CBA | 0.28 | | | | | No Access Credit | 0.26 | Perceived frequency | 0.35 |
| Attendance to trainings | 0.28 | Education level | 0.21 | remittances | 0.27 | | | | | remittances | 0.25 | Drought years | 0.34 |
| Disaster fear | 0.27 | thrust in forecasts | -0.21 | Perceived frequency | 0.27 | | | | | thrust in forecasts | 0.25 | CBA | 0.33 |
| importance of CBA | 0.27 | Importance of fin. aid | -0.23 | forecast | 0.26 | | | | | aid | 0.25 | Effect of neighbours | 0.32 |
| Size cropland | 0.27 | Effect neighbours | -0.23 | intention | 0.26 | | | | | importance of efficiency | 0.24 | Attendance to trainings | 0.32 |
| Drought years | 0.26 | No Location | -0.26 | planning | 0.25 | | | | | forecast | 0.24 | importance of efficiency | 0.32 |
| Effect neighbours | 0.25 | Attendance to trainings | -0.26 | thrust in forecasts | 0.25 | | | | | importance of costs | 0.23 | No Location | 0.29 |
| Income off-farm | 0.25 | aid | -0.28 | importance of trainings | 0.24 | | | | | Income farm | 0.22 | female | 0.28 |
| HHsize +12y | 0.23 | Limited Skills | -0.32 | | | | | | | Limited Skills | 0.21 | Disaster fear | 0.25 |
| CBA | 0.22 | Perceived frequency | -0.33 | aid | 0.21 | | | | | capacity | -0.26 | Size cropland | 0.24 |
| female | 0.21 | perceived efficiency | -0.33 | age | 0.21 | | | | | | | Had credit before | 0.23 |
| measures | -0.22 | No Access Credit | -0.38 | *Attendance to trainings* | *0.21* | | | | | | | Lack Labour | 0.22 |
| importance of actions neighbours | -0.24 | importance of risk | -0.40 | | | | | | | | | HHsize12 | 0.22 |
| Sum measures | -0.26 | importance of costs | -0.40 | Seasons spend in water shortage | *-0.17* | | | | | | | intention | 0.21 |
| Water shortage | -0.29 | importance of efficiency | -0.44 | measures | -0.21 | | | | | | | importance of actions neighbours | -0.22 |
| Size land | -0.33 | Drought years | -0.48 | Faith in god | -0.23 | | | | | | | Size land | -0.32 |
| | | vulnerability | -0.49 | Farm expenses | -0.25 | | | | | | | | |
| | | Lack Labour | -0.49 | | | | | | | | | | |
| | | Disaster fear | -0.50 | No financial help | -0.26 | | | | | | | | |
| | | | | Expenditures off-farm | -0.27 | | | | | | | | |
| | | | | importance of actions neighbours | -0.29 | | | | | | | | |
| | | | | Adaptation spending | -0.32 | | | | | | | | |
| | | | | Climate change fear | -0.43 | | | | | | | | |
| | | | | Total expenses | -0.46 | | | | | | | | |
| | | | | capacity | -0.48 | | | | | | | | |
| | | | | Food expenditures | -0.50 | | | | | | | | |

*Table 3E: Correlation coefficients (R values) for all variables that have a p<0.001 significant relation with the variable on top of the columns (Likert scale importance: from not important at all to essential).*

| **Importance of risk in making decisions** | | **Importance of costs in making decisions** | | **Importance of adaptation efficacy in making decisions** | | **Importance of financial help in making decisions** | | **Importance of extension services in making decisions** | | **Importance of cost-efficiency in making decisions** | | **Importance of neighbours' actions in making decisions** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Importance costs** | 0.74 | importance efficiency | 0.84 | importance costs | 0.84 | Importance Extension | 0.56 | useful trainings | 0.63 | importance | 0.42 | sum measures | 0.30 |
| **importance efficiency** | 0.72 | importance risk percept | 0.74 | importance risk percept | 0.72 | importance costs | 0.55 | information access | 0.60 | Limited Skills | 0.40 | capacity | 0.30 |
| **no. droughts experienced** | 0.60 | perceived efficiency | 0.57 | no. droughts experienced | 0.60 | importance risk percept | 0.50 | useful trainings | 0.56 | useful trainings | 0.40 | effect neighbours | 0.29 |
| **perceived efficiency** | 0.58 | no. droughts experienced | 0.56 | perceived efficiency | 0.53 | information access | 0.49 | Importance fin. aid | 0.56 | information access | 0.38 | measures | 0.24 |
| **Importance fin. aid** | 0.50 | Importance fin. aid | 0.55 | Lack of Labour | 0.48 | useful trainings | 0.46 | respondent | 0.55 | importance costs | 0.37 | adaptation spending | 0.24 |
| **Lack Labour** | 0.46 | information access | 0.47 | Importance fin. aid | 0.45 | importance efficiency | 0.45 | forecast | 0.54 | effect neighbours | 0.37 | farm expenses | 0.23 |
| **Limited Skills** | 0.46 | Lack Labour | 0.44 | Limited Skills | 0.42 | no. droughts experienced | 0.44 | thrust in forecasts | 0.47 | no. droughts experienced | 0.36 | expenditures farm | 0.23 |
| **No Access Credit** | 0.43 | Limited Skills | 0.44 | No Access Credit | 0.39 | forecast | 0.42 | Limited Skills | 0.43 | importance risk percept | 0.33 | information access | -0.22 |
| **perceived frequency** | 0.38 | perceived frequency | 0.43 | perceived frequency | 0.35 | Limited Skills | 0.40 | importance costs | 0.42 | Attendance to trainings | 0.33 | importance efficiency | -0.23 |
| **information access** | 0.38 | Importance extension | 0.42 | effect neighbours | 0.33 | thrust in forecasts | 0.40 | importance CBA | 0.42 | importance efficiency | 0.33 | forecast | -0.24 |
| **farm income** | 0.37 | useful trainings | 0.41 | | | perceived efficiency | 0.36 | size cropland | 0.38 | Limited Skills | 0.32 | perceived frequency | -0.24 |
| **remittances** | 0.35 | forecast | 0.41 | importance CBA | 0.33 | useful trainings | 0.35 | effect neighbours | 0.36 | intention | 0.31 | Importance fin. aid | -0.26 |
| **No Location** | 0.34 | importance CBA | 0.37 | | | perceived frequency | 0.35 | female | 0.35 | perceived efficiency | 0.31 | importance costs | -0.26 |
| | | effect neighbours | 0.35 | information access | 0.32 | respondent | 0.34 | perceived efficiency | 0.34 | respondent | 0.30 | No Access Credit | -0.26 |
| **importance CBA** | 0.33 | No Access Credit | 0.34 | useful trainings | 0.31 | effect neighbours | 0.30 | Attendance to trainings | 0.33 | planning | 0.30 | importance risk percept | -0.27 |
| **useful trainings** | 0.33 | No Location | 0.34 | No Location | 0.30 | No Location | 0.30 | CBA | 0.32 | Importance fin. aid | 0.29 | vulnerability | -0.27 |
| **willingness** | 0.33 | CBA | 0.33 | disaster fear | 0.30 | importance CBA | 0.29 | Income off-farm | 0.32 | useful trainings | 0.28 | no. droughts experienced | -0.29 |
| **forecast** | 0.32 | thrust in forecasts | 0.33 | forecast | 0.30 | remittances | 0.27 | importance risk percept | 0.30 | No Access Credit | 0.28 | Limited Skills | -0.30 |
| effect neighbours | 0.30 | Disaster fear | 0.28 | remittances | 0.29 | Lack Labour | 0.27 | perceived frequency | 0.29 | Edu | 0.28 | Lack Labour | -0.32 |
| Importance extension | 0.30 | willingness | 0.27 | farm income | 0.29 | size cropland | 0.26 | importance efficiency | 0.28 | forecast | 0.27 | | |
| CBA | 0.28 | useful trainings | 0.27 | CBA | 0.29 | disaster fear | 0.26 | Attendance to trainings | 0.28 | perceived frequency | 0.23 | | |
| Attendance to trainings | 0.28 | remittances | 0.26 | Importance extension | 0.28 | No Access Credit | 0.25 | No Location | 0.27 | farm income | 0.23 | | |
| thrust in forecasts | 0.26 | farm income | 0.23 | intention | 0.25 | CBA | 0.24 | no. droughts experienced | 0.24 | thrust in forecasts | 0.23 | | |
| intention | 0.25 | Attendance to trainings | 0.23 | Attendance to trainings | 0.24 | Attendance to trainings | 0.23 | sum measures | -0.23 | No Location | 0.22 | | |
| disaster fear | 0.24 | intention | 0.22 | thrust in forecasts | 0.23 | vulnerability | 0.21 | perceived future | -0.26 | Lack Labour | 0.20 | | |
| age | 0.22 | age | 0.21 | age | 0.22 | Attendance to trainings | 0.20 | water shortage | -0.30 | climate change | -0.20 | | |
| No financial help | -0.25 | climate change | -0.20 | planning | 0.22 | farm expenses | -0.20 | size land | -0.40 | water shortage | -0.20 | | |
| Expenditures off-farm | -0.25 | farm expenses | -0.23 | aid | 0.22 | expenditures farm | -0.20 | | | | | | |
| god | -0.26 | expenditures farm | -0.23 | farm expenses | -0.20 | tot expenses | -0.20 | | | | | | |
| Importance neighbours | -0.27 | No financial help | -0.24 | expenditures farm | -0.20 | sum measures | -0.21 | | | | | | |
| climate change | -0.27 | Expenditures off-farm | -0.25 | food expenditures | -0.18 | capacity | -0.23 | | | | | | |
| tot expenses | -0.40 | Importance neighbours | -0.26 | tot expenses | -0.20 | size land | -0.23 | | | | | | |
| capacity | -0.40 | food expenditures | -0.33 | capacity | -0.23 | measures | -0.25 | | | | | | |
| food expenditures | -0.44 | tot expenses | -0.35 | | | Importance neighbours | -0.26 | | | | | | |
| | | capacity | -0.40 | | | | | | | | | | |

*Table 3F: Mixed logistic regression models investigating policy influence in farmer's intention to adopt individual drought adaptation measures. Significance: p<0.1 . ; p<0.05 *; p<0.01 **; p<0.001 ****

| Household characteristics | Estimate | Pr(>\|z\|) |
|---|---|---|
| *extension.onceperyear* | 0.14 | |
| *extension.onceperseasons* | 0.90 | *** |
| *Ewarning.yearlyoutlook* | 0.57 | ** |
| *ewarning.seasonaloutlook* | 0.94 | *** |
| *transfer.lumpsum* | 0.13 | |
| *transfer.twosums* | 0.21 | . |
| *credit.fivepercentpercent* | 0.41 | * |
| *credit.twopercentpercent* | 0.59 | *** |
| *Business-as-usual* | -5.64 | *** |
| *chol.extension.onceperyear:extension.onceperyear* | 0.88 | ** |
| *chol.extension.onceperyear:extension.onceperseasons* | 0.84 | *** |
| *chol.extension.onceperseasons:extension.onceperseasons* | 1.34 | *** |
| *chol.extension.onceperyear:ewarning.yearlyoutlook* | -0.81 | * |
| *chol.extension.onceperseason:ewarning.yearlyoutlook* | -0.22 | |
| *chol.ewarning.yearlyoutlook:ewarning.yearlyoutlook* | 1.24 | ** |
| *chol.extension.onceperyear:ewarning.seasonaloutlook* | -0.03 | |
| *chol.extension.onceperseason:ewarning.seasonaloutlook* | 1.12 | *** |
| *chol.ewarning.yearlyoutlook:ewarning.seasonaloutlook* | 0.24 | |
| *chol.ewarning.seasonaloutlook:ewarning.seasonaloutlook* | 0.23 | |
| *chol.extension.onceperyear:transfer.lumpsum* | -0.09 | |
| *chol.extension.onceperseason:transfer.lumpsum* | -0.07 | |
| *chol.ewarning.yearlyoutlook:transfer.lumpsum* | -0.18 | |
| *chol.ewarning.seasonaloutlook:transfer.lumpsum* | 0.41 | |
| *chol.transfer.lumpsum:transfer.lumpsum* | 0.77 | * |
| *chol.extension.onceperyear:transfer.twosums* | 0.00 | |
| *chol.extension.onceperseason:transfer.twosums* | 0.17 | |
| *chol.ewarning.yearlyoutlook:transfer.twosums* | -0.49 | . |
| *chol.ewarning.seasonaloutlook:transfer.twosums* | 0.52 | * |
| *chol.transfer.lumpsum:transfer.twosums* | 0.53 | ** |
| *chol.transfer.twosums:transfer.twosums* | 0.14 | |
| *chol.extension.onceperyear:credit.fivepercent* | -0.39 | |
| *chol.extension.onceperseason:credit.fivepercent* | 1.55 | *** |
| *chol.ewarning.yearlyoutlook:credit.fivepercent* | -0.10 | |
| *chol.ewarning.seasonaloutlook:credit.fivepercent* | 0.16 | |
| *chol.transfer.lumpsum:credit.fivepercent* | -0.29 | |
| *chol.transfer.twosums:credit.fivepercent* | 0.19 | |
| *chol.credit.fivepercent:credit.fivepercent* | -0.26 | |
| *chol.extension.onceperyear:credit.twopercent* | 0.19 | |
| *chol.extension.onceperseason:credit.twopercent* | 0.75 | ** |
| *chol.ewarning.yearlyoutlook:credit.twopercent* | -0.29 | |
| *chol.ewarning.seasonaloutlook:credit.twopercent* | 0.35 | |
| *chol.transfer.lumpsum:credit.twopercent* | -0.81 | |
| *chol.transfer.twosums:credit.twopercent* | 0.56 | |
| *chol.credit.fivepercent:credit.twopercent* | -0.09 | |
| *chol.credit.twopercent:credit.twopercent* | -0.13 | |
| *chol.extension.onceperyear: Business-as-usual* | -4.53 | *** |
| *chol.extension.onceperseason: Business-as-usual* | 0.31 | |
| *chol.ewarning.yearlyoutlook: Business-as-usual* | -1.01 | * |
| *chol.ewarning.seasonaloutlook: Business-as-usual* | -1.30 | * |
| *chol.transfer.lumpsum: Business-as-usual* | 0.84 | * |
| *chol.transfer.twosums: Business-as-usual* | 3.00 | *** |
| *chol.credit.fivepercent: Business-as-usual* | 0.75 | |
| *chol.credit.twopercent: Business-as-usual* | 1.49 | * |
| *chol. Business-as-usual: Business-as-usual* | 2.70 | *** |

_Table 3G: Mixed logistic regression models investigating policy influence in farmer's intention to adopt individual drought adaptation measures with multiple farm household characteristics (left) and factors related to the_ PROTECTION MOTIVATION THEORY _and_ THEORY OF PLANNED BEHAVIOUR _(right) as case-specific variables. Significance levels: p<0.1 . ; p<0.05 *; p<0.01 **; p<0.001 ***_

| Household characteristics | Estimate | Pr(>\|z\|) | Behavioural factors | Estimate | Pr(>\|z\|) |
|---|---|---|---|---|---|
| extension | 0.96 | *** | extension | 1.63 | *** |
| ewarning | 0.63 | * | ewarning | 0.97 | *** |
| transfer | -0.11 | | transfer | -0.15 | |
| credit | -0.14 | * | credit | -0.20 | ** |
| asc | -4.32 | *** | asc | -3.45 | *** |
| extension_sizeland | 0.03 | | extension_effect neigbours | -0.12 | * |
| extension_Attendance to trainings | -0.09 | *** | extension_CBA | 0.03 | |
| extension_god | 0.12 | * | extension_nr. droughts experienceds | -0.03 | * |
| extension_membergroup | 0.05 | | extension_totexpenses | 0.00 | |
| extension_summeasures | 0.21 | *** | extension_perceived efficiency | -0.05 | |
| extension_edu | -0.14 | *** | extension_vulnerability | -0.07 | |
| extension_age | -0.01 | ** | extension_capacity | 0.08 | . |
| extension_incomeoffarm | -0.01 | | extension_disasterfear | -0.10 | |
| extension_hhsize | -0.01 | | extension_information | -0.10 | * |
| ewarning_sizeland | 0.02 | | extension_totincome | -0.07 | ** |
| ewarning_Attendance to trainings | 0.04 | | extension_adaptationspending | -0.01 | |
| ewarning_god | 0.01 | | ewarning_effect neigbours | -0.03 | |
| ewarning_membergroup | -0.23 | * | ewarning_CBA | 0.06 | |
| ewarning_summeasures | 0.16 | *** | ewarning_nr. droughts experienceds | -0.02 | |
| ewarning_edu | -0.09 | ** | ewarning_totexpenses | 0.00 | |
| ewarning_age | 0.00 | | ewarning_perceived efficiency | 0.05 | |
| ewarning_incomeoffarm | -0.01 | | ewarning_vulnerability | 0.06 | |
| ewarning_hhsize | 0.00 | | ewarning_capacity | 0.07 | . |
| transfer_sizeland | -0.03 | | ewarning_disasterfear | -0.06 | |
| transfer_Attendance to trainings | 0.00 | | ewarning_information | -0.07 | |
| transfer_god | 0.04 | | ewarning_totincome | -0.06 | * |
| transfer_membergroup | -0.08 | | ewarning_adaptationspending | -0.03 | |
| transfer_summeasures | 0.11 | ** | transfer_effect neigbours | -0.14 | * |
| transfer_edu | -0.01 | | transfer_CBA | 0.14 | . |
| transfer_age | 0.00 | | transfer_nr. droughts experienceds | 0.00 | |
| transfer_incomeoffarm | 0.04 | | transfer_totexpenses | 0.00 | |
| transfer_hhsize | -0.01 | | transfer_perceived efficiency | 0.04 | |
| credit_sizeland | -0.02 | *** | transfer_vulnerability | 0.00 | |
| credit_Attendance to trainings | 0.01 | * | transfer_capacity | 0.02 | |
| credit_god | 0.00 | | transfer_disasterfear | -0.01 | |
| credit_membergroup | -0.08 | ** | transfer_information | -0.07 | |
| credit_summeasures | -0.02 | . | transfer_totincome | 0.01 | |
| credit_edu | 0.02 | ** | transfer_adaptationspending | 0.05 | * |
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| | | | credit_perceived efficiency | -0.02 | |
| | | | credit_vulnerability | -0.01 | |
| | | | credit_capacity | -0.01 | |
| | | | credit_disasterfear | 0.03 | |
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| | | | credit_totincome | 0.01 | |
| | | | credit_adaptationspending | 0.00 | |

# CHAPTER 4:

## SIMULATING SMALL-SCALE AGRICULTURAL ADAPTATION DECISIONS IN RESPONSE TO DROUGHT DISASTER RISK:

## *AN EMPIRICAL AGENT-BASED MODEL FOR SEMI-ARID KENYA*

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## Samenvatting

In Oost-Afrika leiden de toenemende klimaatvariabiliteit en de veranderende sociaaleconomische omstandigheden tot een toename van de frequentie en intensiteit van droogterampen. Droogte vormt een ernstige bedreiging voor de voedselzekerheid in deze regio, die wordt gekenmerkt door een grote afhankelijkheid van – van regen afhankelijke - kleinschalige landbouw en een laag niveau van technologische ontwikkeling in de voedselproductiesystemen. Het toekomstige droogterisico zal worden bepaald door de aanpassingskeuzes van de agrariërs, maar toch zijn er maar weinig droogterisicomodellen die aanpassingsgedrag – het maken van beslissingen over droogtemaatregelen – in het droogterisico integreren.

In dit hoofdstuk gebruiken we een innovatief dynamisch model voor aanpassing aan droogterisico's, genaamd ADOPT, om de factoren te evalueren die van invloed zijn op aanpassingsbeslissingen en de daaropvolgende toepassing van droogtemaatregelen, en hoe dit het droogterisico voor de landbouwproductie beïnvloedt. ADOPT combineert sociaal-hydrologische en agent-gebaseerde modelbenaderingen door het gewasmodel AquacropOS te koppelen aan een gedragsmodel dat in staat is verschillende adaptieve gedragstheorieën te simuleren. In dit hoofdstuk vergelijken we de 'Protection Motivation Theory', die begrensde rationaliteit beschrijft, met een basisniveau uitgaande van geen nieuwe droogtemaatregelen, en een economisch rationeel aanpassingsgedrag. Het opnemen van deze scenario's dient om het effect van verschillende veronderstellingen over adaptief gedrag op de evolutie van het droogterisico in de tijd te evalueren en te vergelijken.

ADOPT is in dit hoofdstuk geparametriseerd aan de hand van veldgegevens verzameld bij 250 huishoudens en gesprekken met plaatselijke besluitvormers in Kitui, een semi-aride provincie in Kenia. De resultaten tonen aan dat schattingen van droogterisico's en de behoefte aan noodvoedselhulp kunnen worden verbeterd met een agent-gebaseerde aanpak: we laten zien dat het negeren van individuele huishoudkenmerken leidt tot een onderschatting van de behoefte aan voedselhulp. Bovendien tonen we aan dat het begrensde rationele scenario beter de historische voedselzekerheid, armoedeniveaus en oogstopbrengsten kan weergeven. We tonen dus aan dat de realiteit van complexe menselijke aanpassingsbeslissingen het best kan worden beschreven door uit te gaan van begrensd rationeel aanpassingsgedrag; bovendien zijn een op agenten gebaseerde aanpak en de keuze van de aanpassingstheorie van belang bij het kwantificeren van risico's en het ramen van de behoefte aan noodhulp.

## Summary

In Eastern Africa, increasing climate variability and changing socioeconomic conditions are exacerbating the frequency and intensity of drought disasters. Droughts pose a severe threat to food security in this region, which is characterized by a large dependency on smallholder rain-fed agriculture and a low level of technological development in the food production systems. Future drought disaster risk will be determined by the adaptation choices made by farmers, yet few drought disaster risk models incorporate adaptive behaviour in the estimation of drought disaster risk.

In this Chapter, we use an innovative dynamic drought disaster risk model, ADOPT, to evaluate the factors that influence adaptation decisions and the subsequent adoption of measures, and how this affects drought disaster risk for agricultural production. ADOPT combines socio-hydrological and agent-based modelling approaches by coupling the FAO crop model AquacropOS with a behavioural model capable of simulating different adaptive behavioural theories. In this Chapter, we compare the protection motivation theory, which describes bounded rationality, with a business-as-usual and an economic rational adaptive behaviour. The inclusion of these scenarios serves to evaluate and compare the effect of different assumptions about adaptive behaviour on the evolution of drought disaster risk over time.

Applied to a semi-arid case in Kenya, ADOPT is parameterized using field data collected from 250 households in the Kitui region and discussions with local decision-makers. The results show that estimations of drought disaster risk and the need for emergency food aid can be improved using an agent-based approach: we show that ignoring individual household characteristics leads to an underestimation of food-aid needs. Moreover, we show that the bounded rational scenario is better able to reflect historic food security, poverty levels, and crop yields. Thus, we demonstrate that the reality of complex human adaptation decisions can best be described assuming bounded rational adaptive behaviour; furthermore, an agent-based approach and the choice of adaptation theory matter when quantifying risk and estimating emergency aid needs.

## 1. Introduction

Droughts regularly affect communities, leading to water and food shortages, reduced crop yields, loss of livelihood, and famine (Barron et al., 2003; Ifejika et al., 2008). The impacts are difficult to quantify because they are often delayed and may last several years (Wilhite, 2000; United Nations Development Programme, 2007). Moreover, the magnitude of these impacts not only depends on the severity of the drought event and the number of people exposed but also on how people adapt to periods of reduced water availability (Mude et al., 2007; Birkmann et al., 2013). Although several studies have dealt with uncertainties in estimating drought hazard, the interplay between adaptation and drought disaster risk has often been neglected (Chapter 2). Consequently, vulnerability has typically been included as a static factor, which assumes a "business-as-usual" level of future adaptation (Adger et al., 2018; De Pinto et al., 2019).

In reality, adaptive behaviour is highly dynamic (Dobbie, 2013; De Koning, 2019). People implement drought adaptation measures based on past experiences and changes in their natural and socioeconomic environment (e.g., Wilhite, 2002; Stefanovi, 2015; González et al., 2016). Understanding the dynamic interplay between the physical water system and human adaptation has sparked the novel socio-hydrology scientific field (Sivapalan et al., 2012; Baldassarre et al., 2015). Recognizing this socio-hydrological feedback is found necessary for better understanding the fluctuations in drought disaster risk over time, driven by a combination of physical drivers (e.g., climate variability), socioeconomic developments, and human adaptive behaviours (e.g., Van Loon et al., 2016; Hagenlocher et al., 2019).

Research has attempted to simulate the adaptive decisions of individuals facing the harmful effects of hazard events using recognized economic theories, such as the expected utility theory (EUT, Von Neumann and Morgenstern, 1945) for economic rational decision-making under uncertainty (e.g., Haer et al., 2019). However, human adaptive behaviour under uncertain conditions is rarely rational (Eiser et al., 2012; Holden, 2015), and people tend to exhibit "bounded rational" logic when deciding on adaptation measures (Asgary and Levy, 2009; Van Duinen et al., 2016). For example, research in disaster risk management has shown people overestimate the probability of rare events, and adaptive behaviour and risk perception are shaped by factors including worry, past experiences, and socioeconomic conditions (Tongruksawattana, 2014; Mwongera et al., 2017).

The existence of bounded rational behaviour has been confirmed by studies on agricultural drought disaster risk (e.g., Van Duinen et al., 2012; Gebrehiwot and van der Veen, 2015; Elagib et al., 2017), evidenced by low adoption of wells and irrigation measures among farmers, despite such measures being economically efficient (Ngigi et al., 2005b; Khisa et al., 2014b; Bouma et al., 2016; Wambua and Akuja, 2016). It has been suggested that farmers' adaptation decisions are influenced by a biased perception of risk and a lack of trust in their own control over drought disaster risk (Murgor et al., 2013; Ochieng et al., 2016; Nkatha, 2017; Khisa, 2018; Van Valkengoed and Steg, 2019). Other factors that have been shown to influence the adoption of adaptation practices include limited access to financial, human, social, natural, and physical capital (Kalungu et al., 2013; Matere et al., 2016; Bunclark et al., 2018). Knowledge dissemination through social networks and the gaining of required skills through extension services are increasingly seen as essential for improving the agricultural drought practices of smallholder farmers (Kitinya et al., 2012; Van Duinen et al., 2016).

Although the importance of including such complex human adaptive behaviour in risk assessments is increasingly recognized (Palmer and Smith, 2014; Groeneveld et al., 2017; Schlüter et al., 2017), identifying the key variables that steer adaptation decisions is difficult (e.g., Klabunde and Willekens, 2016; Aerts et al., 2018). Alternative theories for modelling adaptive behaviour—adding psychological and sociological drivers in addition to economic ones—can be applied to overcome this challenge. Examples of such complex theories include the prospect theory (Kahneman and Tversky, 1979; Asgary and Levy, 2009; Holden and Quiggin, 2017), the theory of planned behaviour (Wheeler et al., 2013; Sutton, 2014; Van Dijk et al., 2016), and the protection motivation theory (Maddux and Rogers, 1983; Grothmann and Patt, 2005). Among these, the protection motivation theory (PMT) is one that has been successfully applied to describe farmers' dynamic drought-adaptive behaviour in multiple studies (Dang et al., 2014b; Gebrehiwot and van der Veen, 2015; Van Duinen et al., 2015a; Keshavarz and Karami, 2016; Zheng and Dallimer, 2016).

In this Chapter, we study the factors that drive drought adaptation decisions of smallholder farmers by comparing business-as-usual and economic rational behaviour—the latter modelled following the EUT–, with the more complex, empirically supported bounded rational behaviour—modelled following the PMT. We developed an innovative dynamic drought disaster risk model, ADOPT, which links the physical crop growth model AquacropOS (FAO, 2009; Vanuytrecht et al., 2014; Foster et al., 2017b) with a behavioural model capable of simulating each of the abovementioned scenarios. ADOPT thus simulates the adaptive actions and interactions of individual farm households in relation to experienced agricultural drought disaster risk. It applies an agent-based approach, the primary tool for modelling individual adaptation decisions and complex interactions (Railsback and Grimm, 2012). In agent-based models (ABMs), agents (e.g., government, households) have the capacity to learn and adapt in response to changes in other agents and the environment (Matthews et al., 2007; Palmer and Smith, 2014). As introduced in Chapter 2, ABMs provide a bottom-up method for tracing behaviour over time and simulate human–human and human–environment interactions at the local level, which can lead to the emergence of patterns at the macro-level (Dobbie et al., 2018). Such models include probabilistic functions that describe the individual behavioural dynamics of heterogeneous decisions-makers with different socio-economic backgrounds, are actively applied to study farmers' behaviour in several contexts, such as drought management and farm innovation (Barreteau et al., 2004; Gunkela and Külls, 2011; Schreinemachers and Berger, 2011; Van Oel and Van Der Veen, 2011; Van Duinen et al., 2012; Blair and Buytaert, 2016). In this Chapter, the ADOPT model framework is showcased for subsistence households in semi-arid rural Kenya over the period 1982–2013. Survey data on household behaviour in Kitui, Kenya were used to create a heuristic understanding of the co-evolution of drought disaster risk and human adaptation decisions and to initialize the agents (farm households) in the model. The intent of this Chapter is not to be predictive; but to demonstrate how an agent-based approach and the choice of behavioural theory affect the estimation of drought vulnerability and risk over time.

The remainder of this Chapter is organized as follows: section Case Study Description introduces the semi-arid study area in Kenya for which the model is calibrated. Section ADOPT Model Description contains the model description detailing both agricultural drought simulations using the FAO crop model AquacropOS, and human decision simulations following three scenarios: business-as-usual, economic rational (expected utility theory), and bounded rational (protection motivation theory). Section Results presents the results of drought disaster risk simulations using ADOPT, and section Discussion provides the discussion and conclusions on how different assumptions on adaptive behaviours influence drought disaster risk estimations.

## 2. Materials and Methods

### 2.1. Case Study Description

The case study is representative for the rural areas of three semi-arid counties, Kitui (30.430 km2, 1.136187 citizens), Machakos (6.043 km2, 1.421.932 citizens), and Makueni (8.008 km2, 987,653 citizens) in south-eastern Kenya (TEGEMEO, 2000; ILRI, 2006; Rapsomanikis, 2010). They are characterized by a dry savannah/warm tropical climate (Njoka et al., 2016). Agriculture in this area is dominated by rain-fed subsistence production systems with households largely dependent on crop and livestock production for income (United Nations Development Programme, 2007; Wambua and Akuja, 2016). Maize remains the most important food crop, and drought-induced yield reductions of maize are largely synonymous with food insecurity and dependence on external aid (Brooks et al., 2005, 2009; Alessandro et al., 2015). High temperatures coupled with unreliable rainfall have caused significant shocks for rural communities in past decades, such as in 1999/2000, 2004/2005, 2010/2011, and 2017/2019 (Erenstein et al., 2011b; Kioko, 2013). Furthermore, extreme temperature and rainfall deficiency events have been occurring on an increasingly frequently basis (FEWSNET, 2010; Khisa et al., 2014a; Government of the Republic of Kenya, 2017; Khisa, 2017).

Kenyan households have a long history of adapting to droughts using traditional and emerging practices (Black et al., 2012; Recha et al., 2012; KEFRI et al., 2014; Shiferaw et al., 2014; Kalungu et al., 2015; Kimani et al., 2015; Gbegbelegbe et al., 2017). An example is the building of Fanya Juu terraces, which are a combination of trenches and sand bunds in sloping cropland to increase the storage of runoff on horizontally created terraces (Biamah et al., 1993; Makurira et al., 2011; Hailu et al., 2012; Muriu et al., 2017; Wolka et al., 2018). Another method is residue mulching, which involves covering the soil surface with plant material to retain soil moisture through reduced evaporation and increased infiltration (Okeyo et al., 2014; Mo et al., 2016; Mfitumukiza et al., 2017; Mugambiwa, 2018). While the maintenance of these two in-soil water storage measures can be demanding in terms of labour, implementation knowledge is available and they do not require large initial investments (Lasage and Verburg, 2015). Irrigation—although highly efficient economically (Nakawuka et al., 2018)—is less popular among smallholder farmers because the implementation of irrigation techniques requires advanced and often costly infrastructure, technical knowledge, and institutional support (Sijali and Okumu, 2002; Ngigi et al., 2005a; Kulecho and Weatherhead, 2006; Ngigi, 2019). Moreover, the amount of surface runoff that many areas receive is too small to irrigate (Barron and Okwach, 2005; Rockström and Falkenmark, 2015). To provide extra water, cost-effective shallow wells can be installed, which can be linked to automated irrigation systems, such as a drip system (Ngigi, 2003; Venzi et al., 2015).

Recently, I administered a survey in the case study area to build an understanding on households' drought vulnerability dynamics and changing capacity to cope with droughts. The data collection method involved administration of a short questionnaire among employees of Kenyan national disaster coordination units (n = 10); semi-structured expert interviews (n = 10) with NGOs, governmental water authorities, and pioneer farmers in the Kitui district in Kenya; and an in-depth questionnaire among smallholder farmers in central Kitui (n = 250). While this questionnaire only provides data about a snapshot in time, questions were focused on the dynamics of vulnerability. Rather than asking only questions related to current practices, the survey was designed to also inquire aspirations, challenges and intentions to adopt new drought adaptation measures in the past and the future. Based on this survey, the following on-farm drought adaptation measures were considered in the present research: (i) the improvement of in-soil storage using mulch cover; (ii) the construction of Fanya Juu terraces; (iii) the digging of shallow wells on property; and (iv) the installation of drip irrigation infrastructure. Currently, mulch, Fanya Juu, well, and drip irrigation techniques are applied by 15, 45, 15, and 5% of households interviewed in the area, respectively. The survey was also applied to create economic household profiles (see ODD+D in Supplementary), estimate the investment and maintenance costs of the measures, and drive the utility functions and decision rules of the ADOPT model.

### 2.2. ADOPT Model Description

ADOPT (Figure 4.1) works on the resolution of a subsistence farm managed by one rural household, and consists of two dynamically linked subroutines: (i) the agricultural model AquacropOS (Foster et al., 2017a), which simulates maize yield based on crop characteristics, soil characteristics, daily weather conditions and farm water management (blue box in Figure 1; subsection Simulating Annual Maize Yield per Farm); and (ii) a behavioural model, which can simulate the adaptation decisions of households assuming either business-as-usual behaviour, or through applying a behavioural theory: the expected utility theory (EUT, assuming economic rational behaviour) or the protection motivation theory (PMT, assuming bounded rational behaviour) (red box in Figure 1; subsection Simulating the Adaptive Behaviour of Subsistence Farmers). This setup allows for the assessment of socio-hydrological feedbacks between farm decisions concerning the level of drought adaptation measures and the drought impacts they experienced (purple arrows; subsection Simulating Annual Drought Impact for Subsistence Farmers): in ADOPT, it is explicitly modelled how drought adaptation measures influence crop yield, which impacts the farm income thus household food security and financial assets, which ultimately alters farmers' risk perception and capacity to adopt new adaptation measures (as detailed impact assessments are highly location-specific and effective adaptation depends on the understanding of drought disaster risk at scales close to which decisions are made, the spatial resolution of the model is at the field scale of the farm households (on average 0.6 ha). A complete model description including an overview, design concepts, details, and decision making, as well as a summary of the input data can be found in the ODD+D in Supplementary of this thesis, following the ODD + D protocol for ABMs (Müller et al., 2013).

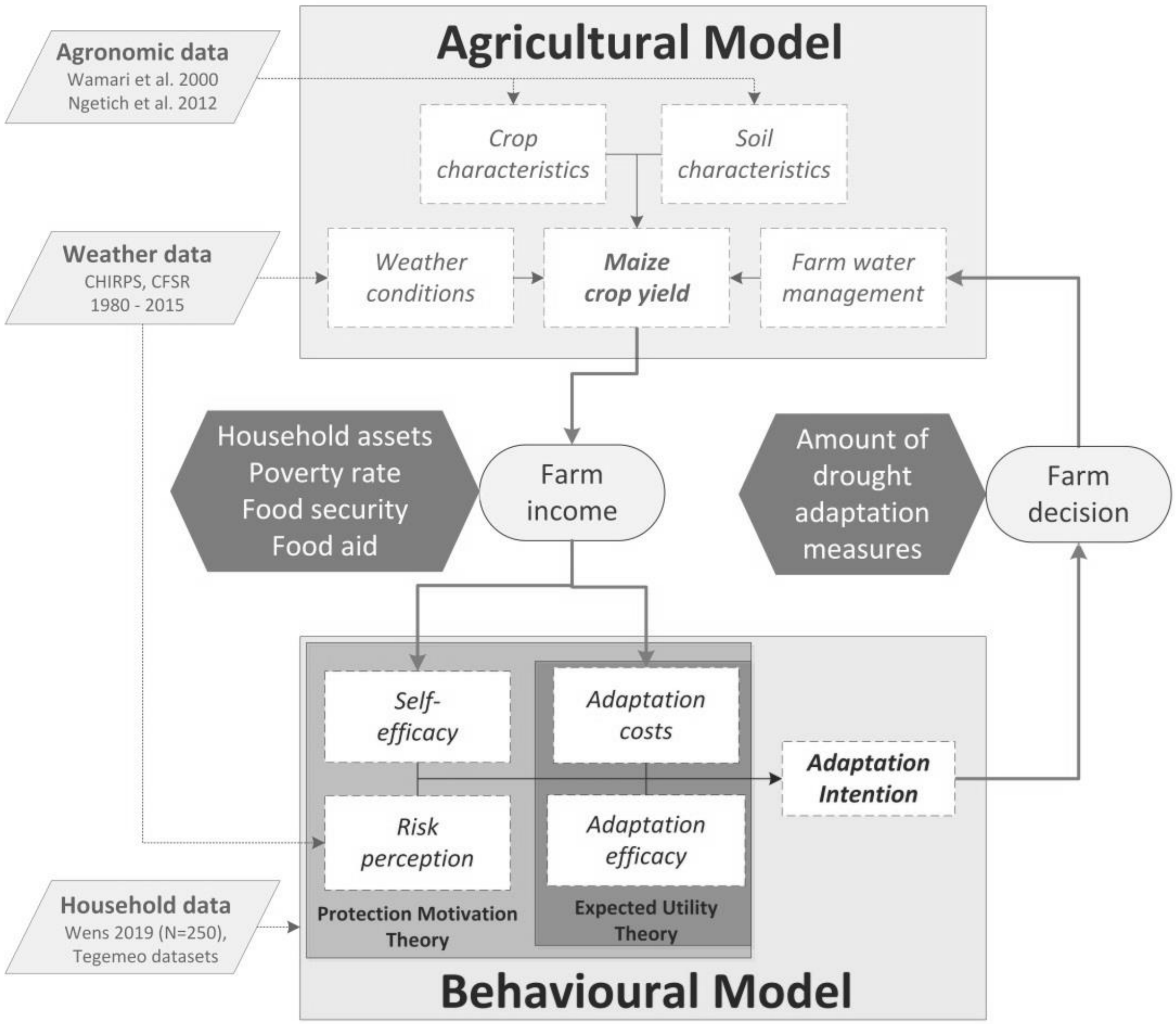


*Figure 4.1. Modelling scheme of the agricultural drought disaster risk adaptation model ADOPT. Seasonal maize crop production is simulated using weather and agronomic data in AquacropOS at the household scale. The resulting household maize yield is translated into farm income, which is fed into a behavioural model. Adaptive behaviour is modelled per farm household using one of three scenarios: No adaptive behaviour, economic rational adaptive behaviour, or bounded rational behaviour. Following expected utility theory, the intention to adapt is modelled to be a function of Adaptation costs, adaptation efficacy, and household assets. Following protection motivation theory, the intention to adapt is a function of risk perception, self-efficacy, adaptation costs, and adaptation efficacy. The individual farm households' intention to adapt leads to the yearly decision whether or not to adopt a new adaptation measure. These adaptation decisions influence their future on-farm water management, thus establishing a feedback. Survey, weather, and agronomic data used as input to the model, whereas yearly risk indicators (household assets, poverty, food insecurity, and food aid) and the adoption rate of drought adaptation measures are outputs of the model.*

### 2.3. Simulating Annual Drought Impact for Subsistence Farmers

To simulate individual crop yield and adaptation decisions over time, a heterogeneous sample of 1,000 farm households in an area of 100 km2, representative for the case of Kitui, Makueni, or Machakos, was chosen to be initialized (Tegemeo Institute, 2000, 2004, 2007, 2010). These households have several characteristics that influence their annual harvest, adaptation decisions, and drought vulnerability, including family and farm size, social network, access to extension services, possible adaptation measures, and off-farm income sources. All household characteristics were stochastically derived from the averages and standard deviations of different household characteristics in previous research and a questionnaire (n = 250) performed as part of this research (Chapter 3). The average farm size is 0.6 ha, heterogeneously distributed among the households. Other spatial characteristics, such as proximity to a river of town were omitted, as they do not influence the model variables. To simulate seasonal market volatility in response to maize availability, the average maize price of Kitui Town market (US$0.35/kg) was weighted by comparing the percentage of total seasonal harvest with the average (30 years) harvest in the study area. From this, maize prices fluctuate between US$0.2/kg (favourable seasons) and US$0.5/kg (seasons with drought-induced crop losses; (Winter-nelson and Amegbeto, 1998; Nyoro et al., 2005; FEWSNET, 2018).
ADOPT runs as follows:

- For each season and household, maize production is simulated using AquacropOS (subsection 2.2.2) based on daily weather conditions as well as the drought adaptation measures applied by the households. This maize harvest is partly allocated to account for the households' food needs—estimated as 103 kg per year per adult (DTMA, 2015) and any additional harvest is sold (farm income, increasing the households' financial assets). Shortages are made up through purchasing (reducing the households' financial assets) at the maize price of the simulated season.
- Each year, all households spend money on non-food and farm input (expenditure), reducing their financial assets, and have a potential off-farm income source (e.g., casual labour, livestock breeding, private business, and brick making) that increases their financial assets. Moreover, based on demographic data, a household could increase or decrease in size over the simulation period, altering its food demand (demographic numbers are based on the survey results).
- Each year, all households evaluate their intention to adopt a new drought adaptation measure. This intention is influenced by the household's financial assets and the behavioural rules of the scenario applied (subsection Simulating the Adaptive Behaviour of Subsistence Farmers). The adoption of such measures influences the households' individual maize production in the following years.

To express the direct and indirect effects drought disaster risk, it is chosen to track, in addition to agricultural production, the following metrics in ADOPT:

- Poverty (households) is calculated per household assuming a poverty line of US$ 1 per day
- Food insecurity (households) occurs if households' food needs exceeds their maize production
- Food aid (US$) is estimated as the food shortage of all households multiplied by the maize price.

The cumulative amount of food shortage (kg) is estimated following two procedures. The first excludes the agent-based approach, assuming all farm households have the same farm area, number of family members, and are equally wealthy (and rich enough to buy their food needs). In this procedure, food shortage is calculated by examining how many households the total regional food supply (sum of the harvest for all households) could feed. Food shortage is thus the difference between supply and needs. The second includes the agent-based approach and food shortage is calculated on an individual household level. Food shortage occurs if households are in food insecurity, and if they do not have the financial means to meet their needs or if the regional food supply does not allow them to buy the extra maize required to fulfil their food needs. The difference between the two procedures helps exemplifying the added value of an agent-based approach.

### 2.4. Simulating Annual Maize Yield per Farm

The open source version of the FAO crop-water model AquacropOS, AquacropOS (Steduto et al., 2009, 2012; Foster et al., 2017a; Foster and Brozović, 2018), was used to simulate biomass and harvestable yield responses of maize to water availability (Vanuytrecht et al., 2014). The model is designed for regions with water-limited agricultural production, such as semi-arid Kenya. By explicitly modelling the plant growth up to harvestable yield, AquacropOS enables the assessment of the effects of water and agricultural management on crop production (Heng et al., 2009). It has been used by numerous studies in Kenya (e.g., Ngetich et al., 2012; Wamari et al., 2012; Omoyo et al., 2015).

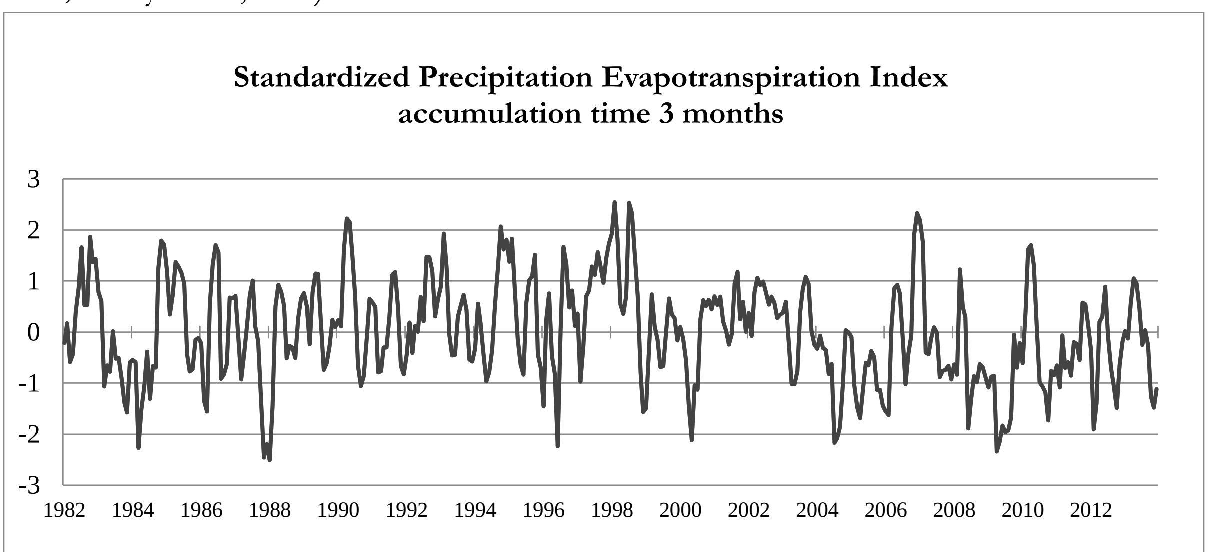


*Figure 4.2. Standardized Precipitation Evaporation Index (SPEI) calculated using CHIRPS Precipitation data and CFSR Evaporation data for 1982–2013. An accumulation time of 3 months was used to show the seasonal climate variability. Values below 0 indicate conditions dryer than average. If such dryer than average conditions are prolonged and occur during the crop growing cycle, drought impacts on agricultural production can be expected.*

Historical weather data (1981–2013; Figure 4.2) for Kitui were used as input for AquacropOS, which includes the daily gridded CHIRPS rainfall dataset (Funk et al., 2015b), which combines 0.05° resolution satellite imagery with in-situ station data. Furthermore, daily minimum and maximum temperature (°C), relative humidity, wind speed (m/s), and solar radiation (s) from the Kitui area were obtained from the Climate Forecast System Reanalysis (CFSR) dataset from the National Center for Environmental Prediction of the United States National Oceanic and Atmospheric Administration (Dile and Srinivasan, 2014). These data were employed to calculate reference evapotranspiration using the Penman–Monteith equation (Allen, 2004; Ayugi et al., 2020).

Maize-specific parameters, such as the duration of flowering and number of plants per hectare were derived from Ngetich et al. (2014) and Wamari et al. (2012), who conducted an extensive study on the calibration and validation of AquacropOS for Katumani maize in Kenya. Remaining factors were calibrated to obtain realistic crop yield in the range (700–1,200 in good years) reported by Brooks et al. (2009). The period of cropping (growing period of 75–180 days) is limited to the rainy seasons (May–June and October–February) (Government of Kenya, 2007; Black et al., 2012; Mo et al., 2016). The hydraulic properties of the soil were adopted from the case study in semi-arid Kenya executed by Ngetich et al. (2014).

To simulate the effect on crop yield for the four drought adaptation measures discussed, AquacropOS was run for all possible combinations of these measures: It is possible for a household to have a well, perform manual or drip irrigation, and/or have Fanya Juu terraces, and/or apply mulch to fields simultaneously (see section Case Study Description). Here it was assumed that households who apply mulch to their fields were assumed to have a year round 50% coverage of mulch, which AquacropOS converted to a lower evaporation from the soil by 0.6 (Raes et al., 2012). Households with Fanya Juu terraces were assumed to have contour pits and bunds with a height of 60 cm (Wolka et al., 2018). Households with a shallow well are assumed to manually water their crops in times of deficit; the maximum irrigation depth was set at 12 mm, the wetted area was set at 30%, and the soil moisture target was set at 40% depletion (Filho and de Trinchera Gomez, 2018). Since no distributed hydrological model was included, wells are assumed to provide enough water for irrigation at any time, not influenced by the digging of other wells in their surroundings or by long-lasting droughts. In our AquacropOS setup, we assumed that manual watering was a soil moisture-based technique: households will water their field if it feels dry (below 50% of total plant available water). Furthermore, the application efficiency was assumed to be rather low: 45% for manual watering (Howell, 2003). Drip irrigation infrastructure allows for daily irrigation but can only be implemented if a shallow well is already installed. The application efficiency was set to 90% (Kenya Ministry of Environment, Water and Natural Resources and Kenyan Water Resources Management Authority, 2013). Results of the AquacropOS pre-runs showed that crop yields averaged to 0.5 (±0.25) t/ha under no adaptation measures; 0.6 (±0.25) t/ha under mulching or terraces; 0.8 t/ha using manual irrigation; and 1 t/ha using drip irrigation.

### 2.5. Simulating the Adaptive Behaviour of Subsistence Farmers

In ADOPT, three different behavioural scenarios were explored (see Table 4.1): (1) business as usual (BAU); (2) economic rational behaviour [following expected utility theory, EUT]; and (3) bounded rational behaviour [following the Protection Motivation theory, PMT (e.g., Grothmann and Patt, 2005; Dobbie, 2013; Dang et al., 2014a,b; Gebrehiwot and van der Veen, 2015; Stefanovi, 2015; Van Duinen et al., 2015a,b, 2016; Keshavarz and Karami, 2016; Zheng and Dallimer, 2016)]. The BAU and EUT scenarios reflected the common assumptions of no or full economic rational adaptive behaviour in drought disaster risk models, and helped to position the more complex, empirically observed bounded rational behaviour (PMT).

*Table 4.1: scenarios used in the ADOPT model*

| | BAU scenario<br>**Section 2.2.3.1** | EUT scenario<br>**Section 2.2.3.2** | PMT scenario<br>**Section 2.2.3.3** |
|---|---|---|---|
| **Adaptive Behaviour** | Business as usual | Economic rational | Bounded rational |
| **Theory** | / | Expected Utility Theory | Protection Motivation Theory |
| **Adaptation decisions** | No implementation of new adaptation measures; static representation of vulnerability | Implementation based on net present value of adaptation costs, and benefits (yearly gains) over ten year | Implementation influenced by risk appraisal, perceived self-efficacy, perceived adaptation efficacy and adaptation costs |

### 2.6. Business as usual: no new adaptation

To represent the case of risk negligence, no additional adaptation decisions are made by households in the BAU scenario. This suggests that households do not perceive any change in risk or see no benefit in adaptation, and hence will act independently from it. Households have an initial level of drought adaptation (see ODD+D in Supplementary) which does not change over time. It was assumed that these farmers take loans to maintain the measures if needed. The use of this scenario helps position the dynamic-adaptation approach in drought disaster risk assessments.

### 2.7. Economic rational behaviour: expected utility theory

The EUT assumes that people seek to maximize their preferences for safety or risk, evaluating the value ascribed to the outcomes ("the utility") of different adaptation actions and the probability that each will occur (Haer et al., 2016a; Schlüter et al., 2017). Applied to the Kenya case of drought management, rational households are fully self-interested, have full information about expected gains and losses, and always choose the adaptation option that gives the highest utility within their budget constraint. Households evaluate costs (e.g., possible yield loss and installation costs of drought adaptation measures) and benefits (e.g., reduction in possible yield loss) and their associated probabilities objectively and attempt to maximize their expected utility given these costs and benefits (Shaw and Woodward, 2008). Social behaviour, habits, and norms are ignored, and suboptimal choices are not considered (Gigerenzer and Goldstein, 1996). It was also assumed that these farmers (as in BAU) cannot lose measures as they take loans to maintain them if required. The use of this scenario helps position the bounded rational adaptation approach in drought disaster risk assessments.

Based on the AquacropOS pre-runs for all combinations of each of the four adaptation measures, the yield gains (B) calculated as the difference in losses between situations with- and without additional measures as well as the drought probability (p) were derived. Wealth (W) is an individual household variable tracked over time. Implementation and maintenance costs (C) of the adaptation options were obtained from experts in the fields. Assuming a slight risk adversity among the households, the general utility function applied in model is U (x) = ln x, which is a function with constant relative risk aversion. As is generally done in studies applying the EUT (e.g., Haer et al., 2016b), Every year, households adopt the adaptation measure with the highest expected utility (Equation 1), if its action utility proved higher than the utility of no action over a period of 10 years and if they can afford the initial implementation costs.

$$ExpectedUtility_{action} = p * LN(W - C + B_d) + (1 - p) * LN(W - C + B_n) \qquad Eq. 1$$
$$ExpectedUtility_{no\ action} = p * LN(W) + (1 - p) * LN(W)$$

*where*

- p, the probability of a drought season—defined as a season with SPEI-3 value $< -1$.
- W, the wealth (total assets in USD) of the household.
- C, the cost of the adaptation measure in USD.
- B, the benefits (yield gain) in drought years (Bd) and non-drought years (Bn) in USD.

### 2.8. Bounded rational behaviour: protection motivation theory

the EUT has been recognized as having limitations because of the assumptions of full information and the lack of social interactions (Van Duinen et al., 2012). Bounded rational behaviour, influenced by social, economic, and psychological factors, can be included either by adding it to the utility maximization functions or by choosing alternative theories. the use of the PMT, which has been proven to be a valuable tool for understanding the adaptation decisions of individuals under drought disaster risk, backed up by stakeholder surveys in lower-income countries (subsection Bounded rational behaviour: protection motivation theory). This socio-cognitive model of bounded rational private adaptation integrates the effect of available resources and perceived climate risks into one framework for explaining the determinants of individual adaptation (Floyd et al., 2000; Grothmann and Patt, 2005). Indeed, the inclusion of socioeconomic and cognitive factors has been supported by a number of local case studies, which have found off-farm employment, group membership, labour availability, access to extension services, and farm experiences, to be the main drivers for the adoption of drought adaptation measures (e.g., Mutune et al., 2011; Jager and Janssen, 2012; Oremo, 2013; Mutua-Mutuku et al., 2017; Mutunga et al., 2017; Shikuku et al., 2017). Furthermore, the survey in Kitui confirmed that the factors included in PMT are indeed key determinants for the adaptive behaviour in the face of agricultural drought disaster risk (Chapter 3).

PMT states that a person's intention to adapt is formed through the risk appraisal process, and coping appraisal process (Grothmann and Patt, 2005; Bubeck et al., 2012). While the PMT is a qualitative theory, in ADOPT we have formalized this theory, assigning a value between 0 and 1 to all factors of the theory, while allowing room for uncertainties in the form of varying weights for all the factors. In ADOPT, all the individual households form an intention to adapt (Equation 2), a certain adaptation measure (m), on an annual basis (t) as follows:

$$IntentionToAdapt_{t,m} = \alpha * RiskAppraisal_t + \beta * CopingAppraisal_{t,m} \qquad Eq. 2$$

If a household has the financial capacity to pay for a considered measure (Stefanovi, 2015), the intention to adapt is translated into the likelihood the household will adopt this measure in the following years. Whether the household actually adopts the measure is stochastically determined for each household, each year, based on this likelihood. When households have adopted a measure, they will keep the measure. They are assumed to take a loan if they cannot pay then maintenance costs: not maintaining a measure is assumed to double the maintenance costs for the following year.

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

Risk appraisal (Equation 3), in our model-application a value between 0 (not aware of any risk) and 1 (frequently exposed to risk and lost all crop yield last year due to drought), is formed by combining the perceived risk probability and perceived risk severity, shaped by rational and emotional factors (Deressa et al., 2009, 2011; Van Duinen et al., 2015b). Whereas risk perception is based in part on past experiences, several studies have suggested that households place greater emphasis on recent harmful events (Gbetibouo, 2009; Rao et al., 2011; Eiser et al., 2012). To include this cognitive bias, each household has a drought disaster memory, defined as follows (Viglione et al., 2014).

$$RiskAppraisal_t = RiskAppraisal_{t-1} + (\ Drought_t * Damage_t\ ) - 0.125 *\ RiskAppraisal_{t-1}$$
$$with\ \ Damage_t = 1 - exp(-harvestloss_t) \qquad Eq. 3$$

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 damage of a household is related to their harvest loss during the drought year, which is defined as the difference between their current and average harvest over the last 10 years.

Coping Appraisal (Equation 4, in our model-application a value between 0 (no appreciation of the adaptation options at all, no ability to pay for the measures) and 1 (full trust in own capacity, in the efficiency of the measures and easily able to pay for it) represents a households' subjective "ability to act to the costs of a drought adaptation measures, given the adaptation measures' efficiency in reducing risk" (Stefanovi, 2015; Van Duinen et al., 2015a). In ADOPT, coping appraisal is a combination of the households' perceived Self-Efficacy (financial, labour, and knowledge capacity of the farming households), adaptation efficacy (or response efficacy) of the measure, and its adaptation costs (or response cost):

$$CopingAppraisal_{t,m} = \gamma * SelfEfficacy_t + \delta * AdaptationEfficacy_{t,m} + \varepsilon * (1 - Adaptationcosts_t) \qquad Eq.4$$

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

The Adaptation Costs of the possible measures (see ODD+D in Supplementary) were expressed in terms of a percentage of the households' assets (value between 0 and 1, with a maximum of 1 as this reduces the intention to adapt to 0).

The Adaptation Efficacy (value between 0 and 1) of each measure was calculated as the percentage of yield gain, with a maximum of 100%. Because a lack of information is a significant barrier to the adoption of drought adaptation measures (Deressa et al., 2009; Ifejika, 2010; Below et al., 2012), this expected yield gain was estimated for two types of households: those that receive regular extension services (training in farm practices by the government or NGOs) and those that do not:

- For households that receive extension services (randomly assigned during model initialization), the expected yield gains were calculated as the change in annual average yield after the adoption of the drought adaptation measure, using estimates from pre-runs of AquacropOS. Therefore, this assumed prior, unbiased knowledge about the efficacy of adaptation measures.
- Households without access to extension services had to rely on their neighbours to obtain information on adaptation efficacy, and their expected yield gain was estimated as the difference between the yields of neighbouring households that had already adopted a specific measure and the households' own current yield. These households thus have a biased adaptation efficacy.

A meta-analysis of factors motivating climate change adaptive behaviour found that perceived self-efficacy was strongly associated with adaptation decisions (Van Valkengoed and Steg, 2019). In this research, we assumed that younger household heads, household heads with a higher education (human capacity), larger households (labour), and female household heads have a higher self-efficacy (value between 0 and 1) and thus are more likely to adopt the adaptation measures (Oremo, 2013; Charles et al., 2014; Tongruksawattana, 2014; Muriu et al., 2017).

### 2.9. Model Sensitivity

ADOPT was run 50 times per adaptive behavioural scenario in a Monte-Carlo simulation to average the effect of the initialization of household characteristics (household size, farm-size, age, education, off-farm income, and expenditures). To support generalizability and simplicity, these household characteristics were stochastically determined at the start of each run, assuming a normal distribution, with the averages and standard deviations of household characteristics reported in the survey datasets (Chapter 3). Moreover, the bounded rational scenario in ADOPT was run 48 × 50 times, with 6 × 8 differentiating combinations of weights for the Risk Appraisal and Coping Appraisal factors ($\alpha$, $\beta \in [0.334:0.666]$, sum always equals 1) and the Self-Efficacy, Adaptation Efficacy, and Adaptation Costs factors ($\gamma$, $\delta$, $\varepsilon \in [0.25:0.50]$, sum always equals 1). Since it was not possible to calibrate the weights of all PMT factors (this would require more surveys over a long period of time), this sensitivity assessment where each factor was halved or doubled in importance, was conducted to explore the possibility space when accounting for bounded rational behaviour.

Besides, it was also investigated what the effect of the share of households receiving extension services on the outcome would be. This is done because the survey results (60%) and the literature (often estimated around 30%, e.g., TEGEMEO datasets) strongly disagreed on the amount of households who have a correct idea about the costs and benefits, and do not rely on their neighbours to show how measures should be implemented).

## 3. Results

In this section, the results of the ADOPT model runs are presented to explore the difference in adoption rate of drought adaptation measures under BAU, economic rational behaviour (EUT), and bounded rational (PMT) behaviour (section Adoption of Drought Adaptation Measures). Moreover, we investigate the difference in maize harvest and financial assets of the households in the three scenarios (section Maize Harvest and Financial Assets), and the consequences of this on the evolution of drought disaster risk over time in the form of poverty rates, household food insecurity, and food aid needs (section Drought disaster risk).

### 3.1. Adoption of Drought Adaptation Measures

Using the three behavioural theories, ADOPT simulated the intention to adopt and the resulting adoption rate of adaptation measures over time. Based on a pre-run in AquacropOS, it is clear that a combination of all four measures is the most effective way to reduce negative impacts of droughts on crop yield, while a combination of a well with irrigation is the most economic efficient solution. Figure 4.3 shows the adoption rate of the four different drought adaptation measures by the modelled households. Applying mulch to the fields was a cheap and economic efficient adaptation option, and therefore its adoption in the economic rational scenario reaches 81% after 5 years (Figure 4.3, upper left panel). In contrast, a gradual adoption was found in the bounded rational simulation, reaching 34% (11–49%) adoption by the end of the simulation period. The adoption in this scenario is influenced by the households' risk perception as can be seen in the steep increase in the application of mulch during and after the 1999–2000 drought. Fanya Juu terraces, an indigenous technique already applied by 25% of the farmers at the start of the simulation, were very popular (Figure 4.3, upper right panel). An immediate adoption of 85% was seen in the economic rational simulation, and a gradual adoption up to 43% (35–53%) after 30 years was seen in the bounded rational simulation. The installation of a shallow well is economically efficient but expensive, which led to less overall and more gradual adoption in the economic rational and bounded rational scenarios. Households prefer to install a well and then install drip irrigation (Figure 4.3, bottom panels): first they apply manual irrigation, and after saving money they are able to buy drip irrigation infrastructure. Overall, 44 and 10% (3–20%) of the economic rational and bounded rational households were able to install a well, which could drastically increase their crop yields. In general, the households with a larger farm were the ones able to adopt this technique. Furthermore, 43% of all economic rational households and 5% (1–11%) of the bounded rational households were able to then further reduce their drought vulnerability by adopting drip irrigation by 2010.

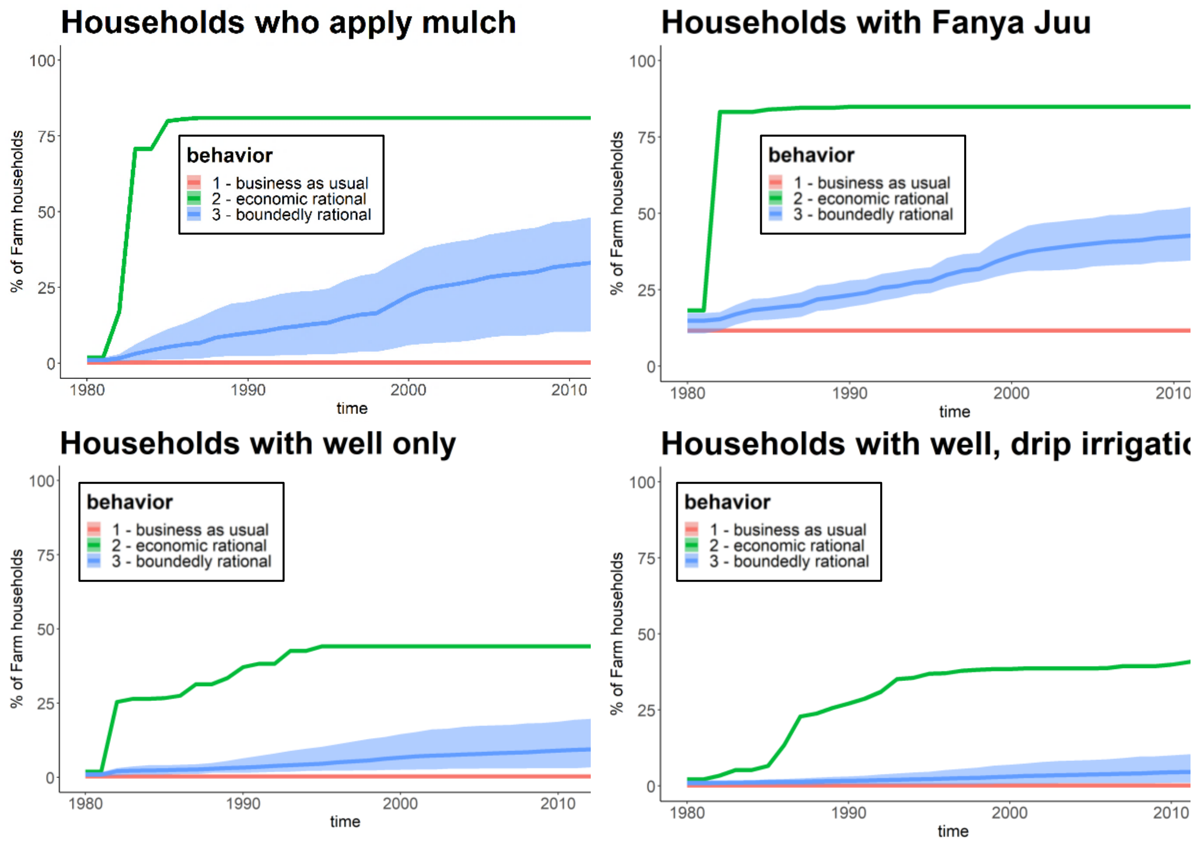


*Figure 4.3. Adoption of different drought adaptation measures over time, for three behavioural scenarios—economic rational (EUT, green), bounded rational (PMT, blue), and business as usual/no adaptation (red)—and for four different drought adaptation measures (Fanya Juu terraces, mulching, manual irrigation and drip irrigation). Shaded blue areas show the variance across 48 bounded rational model runs, a result of the variety in weights of the PMT factors.*

In the bounded rational scenario, adoption occurred gradually since households that do not receive extension services cannot adopt measures they do not see in use in their neighbours' fields. Bounded rational farmers also adopted less economically efficient measures as their limited information reduced their ability to calculate the costs and benefits of all adaptation options. Given the observed adoption rates (Chapter 3) of Fanya Juu terraces (45%), mulching (12%), well construction (16%), and drip irrigation techniques (6%), we find that the economic rational scenario largely overestimated the adaptation of all measures. Besides, in this scenario, we see that after 30 years, 42.5% of the households adopted one measure, 19.5% adopted two, 3% households adopted three and only 0.5% households adopted all four measures. From the survey, it is reported that 42.3% of the respondents adopted one measure, 12.3% adopted two, 1.5% adopted three and 0.7% adopted all four measures. The estimated adoption rates using bounded rational scenario thus best reflected the observations, except in the case of mulch application. The inclusion of PMT behaviour is thus better able to capture some of the variability in adoption decisions but is nevertheless still not a complete explanation of the observed adaptive behaviour of households in semi-arid Kenya.

### 3.2. Maize Harvest and Financial Assets

Figure 4.4 presents the ADOPT average maize harvest results (in kg, based on two growing seasons) for the three behavioural scenarios. These maize harvests were affected by drought events (orange bars) and the adoption of drought adaptation measures over time. The results showed that the historical drought disasters registered in EMDAT (1984, 1991/1992, 1994, 1999/2000, and 2008/2009) were also apparent in our modelled harvest, boosting confidence in the capacity of ADOPT to simulate maize harvest variability. The highest harvest numbers were achieved by economic rational households, which proactively invest in the most economically efficient adaptation measures. Economic rational drought management leads to a more efficient adaptation strategy, and thus lower vulnerability to water shortage and higher average maize production compared with bounded rational drought management. When comparing the bounded rational and BAU scenarios, the bounded rational households yielded greater harvests over time. They adopted adaptation measures mostly after experiencing droughts, thereby gradually moving away from the BAU scenario.

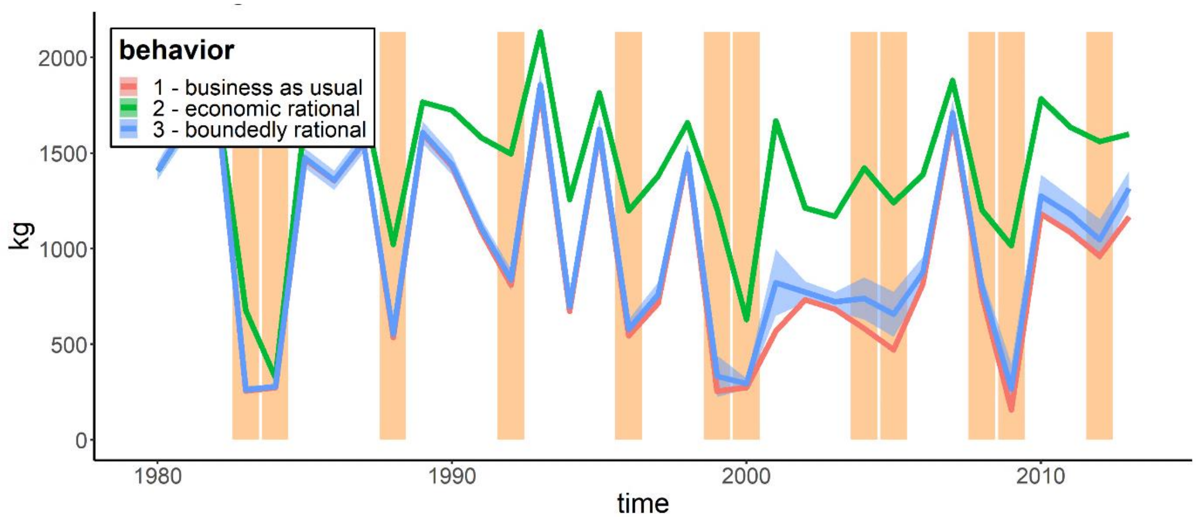


*Figure 4.4. Average annual maize harvest of the modelled households in kg/year for three behavioural scenarios: no adaptation decisions (BAU), economic rational (EUT), and bounded rational (PMT). Drought years (SPEI3 value in crop season < −1) are visualized as vertical orange bars. The shaded area show the variance among 48 bounded rational model runs, a result of the variety in weights of the PMT factors.*

The average harvest varied by ~1,467 kg under economic rational conditions, 992 kg (935–1,062 kg) under bounded rational conditions, and 919 kg under BAU conditions. The average crop yield was 614 kg/ha (591–644 kg/ha) under the bounded rational scenario, whereas it elevated to 805 kg/ha when assuming economic rational households and decreased to 583 kg/ha when assuming BAU households. The bounded rational simulation numbers were close to the observed values in Kitui of 680 kg/ha (605 kg/ha with outliers (biased answers of the survey) removed) (Chapter 3).

The adoption of drought adaptation measures and resulting yield gains has a prominent effect on the household's wealth over time (Figure 4.5). Although adaptation initially required a large investment, thereby reducing financial assets, it is economically efficient in the long turn. This is most clear in the economic rational scenario, where a high initial adoption happens in 1981, and a return on investment after ~12 years, resulting in much wealthier households compared with the business-as-usual rational scenario. The more gradual adoption in the bounded rational scenario only results in an initial decrease, then a slight increase in average wealth, as compared to the BAU scenario. Besides, also droughts have a pronounced effect on a household's wealth over time, as illustrated by the sharp decline in wealth during and following the consecutive droughts of 1983–1984, 1999–2000, and 2004–2005. The increased frequency of severe droughts, starting with the millennium drought, had a distinct effect on the households in the bounded rational and BAU scenarios. The economic rational scenario households proved more resilient to these shocks, as majority of the farmers are able to adopt irrigation infrastructure resulting in an almost constant increase in wealth over time.

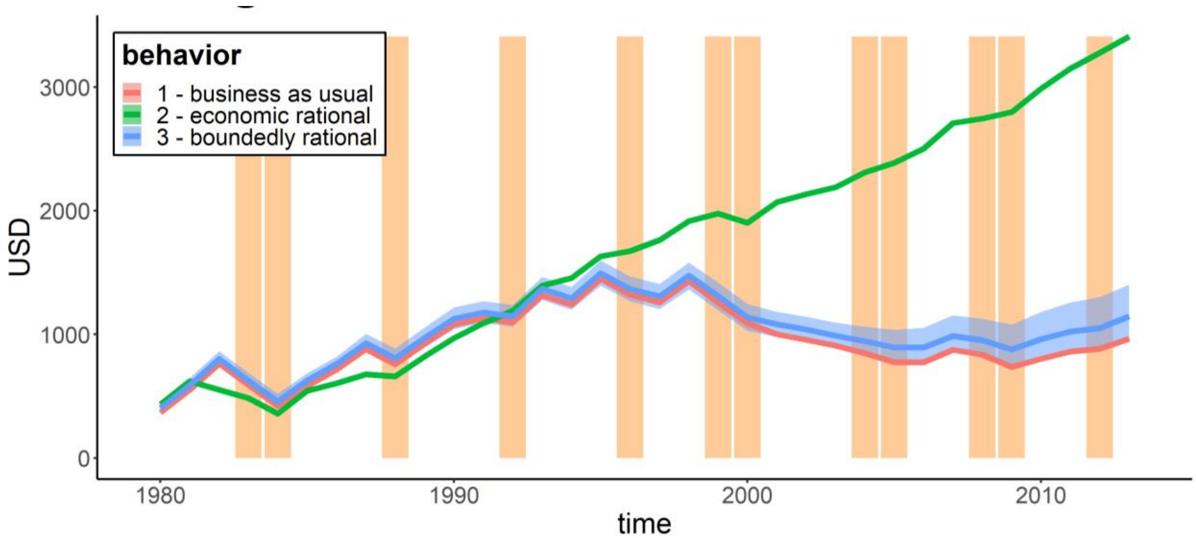


*Figure 4.5. Households' financial assets (in US$/year) over time. Visualized is the median assets stock of all households modelled for three scenarios: no adaptation decisions (BAU), economic rational (EUT), and bounded rational (PMT) adaptive behaviour. Drought years (SPEI value in crop season < −1) are visualized as vertical orange bars. The shaded blue area shows the variance among 48 bounded rational model runs, a result of the variety in weights of the PMT factors.*

### 3.3. Drought disaster risk

As expected, droughts have a negative effect on household food security (Ifejika et al., 2008; Erenstein et al., 2011a), whereas drought adaptation measures have a neutralizing effect. Figure 4.6 shows that the peaks in food insecurity in the economic rational scenario were significantly lower than those of the BAU scenario, the food insecurity rate in the bounded rational scenario slightly reduced over time compared with BAU. This highlights that economic rational households are less food insecure compared with bounded rational households because of their relatively large uptake of adaptation measures before a drought event. However, the resilience to droughts of bounded rational households was higher compared with the BAU scenario; that is, they were less food insecure during and after drought years. On average, 44, 39 (36–43%), and 30% of the households lived in food insecurity in the BAU, bounded, and economic rational behaviour scenarios, respectively. Food insecurity rates in the bounded rational scenario aligned with (Ulrich et al., 2012) who reported a food insecurity rate of 15% in normal years (on average 17% in the bounded rational scenario)—with a sharp outlier to 91% in the 1999–2000 drought and subsequent years (87% in the bounded rational scenario).

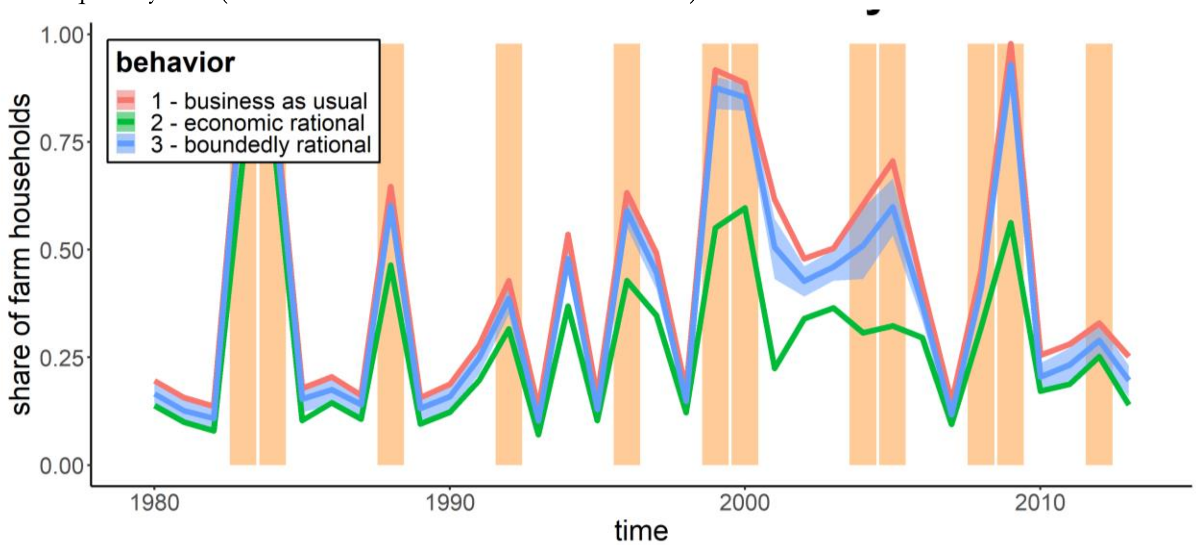


*Figure 4.6. Share of households in food insecurity over time. Variability over time visualized for three behavioural scenarios: economic rational (EUT), bounded rational (PMT), and no adaptation decisions (BAU). Drought years (SPEI value in crop season < −1) are visualized as vertical orange bars. The shaded blue area shows the variance among 50 bounded rational model runs, a result of the variety in weights of the PMT factors.*

The ADOPT results presented in Figure 4.7 show averages of 35, 45 (41–49%), and 49% of the households in poverty under the economic rational, bounded rational, and BAU scenarios, respectively. These estimates were similar to the 46% reported in rural areas by the (Kitui County, 2013). Drought shocks have a profound effect on the poverty level, as can be clearly seen during the recent drought of 2008–2009, when 80% of all households fell into poverty conditions after being hit. The effect of droughts on poverty was also observed by (Few et al., 2006; Mwongera et al., 2013). Notably, our results exhibited an overall increase in poverty while the average financial assets increased through time. The standard deviation of households' maize harvest and financial assets widened over time, which could be a sign that inequality in wealth increased.

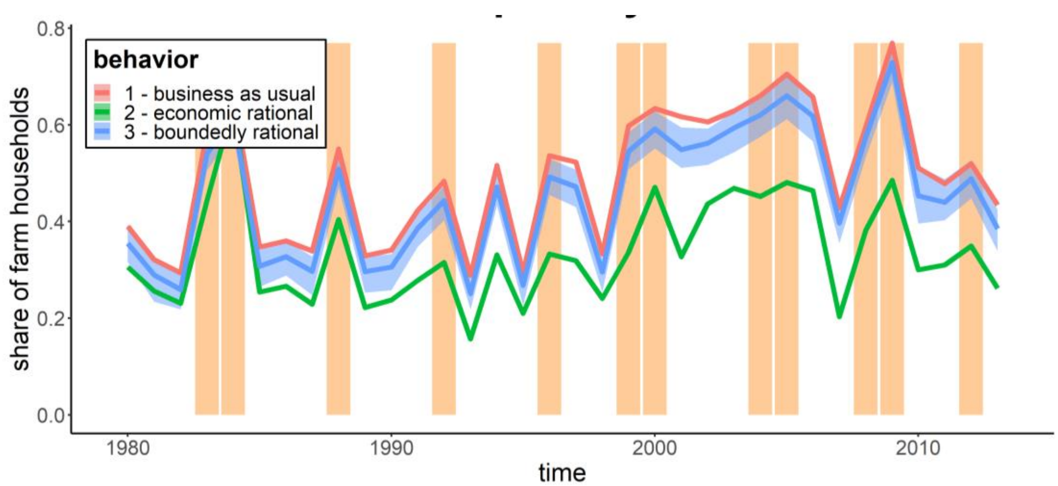


*Figure 4.7. Share of households in poverty. Variability over time is visualized for three behavioural scenarios: economic rational (EUT), bounded rational (PMT), and no adaptation decisions (BAU). Drought years (SPEI value in crop season < −1) are visualized as vertical orange bars. The shaded blue area shows the variance among 50 bounded rational model runs, a result of the variety in weights of the PMT factors.*

Tracking individual households over time, ADOPT showed that it was predominantly the rich households that were able to optimize their drought management, produce more, become richer over time, and thus be able to adopt even more drought adaptation measures. By contrast, less wealthy households did not succeed in adopting sufficient drought adaptation measures, suffered more from large drought impacts, and thus stayed poor. This is clear from Figure 7 where, although gradual adoption happens, poverty levels do not decrease over time: This can be attributed to the "poverty trap effect" (Muyanga, 2004; Mango et al., 2009) as identified by (Ifejika et al., 2008; Ulrich et al., 2012). This is also evident when evaluating the average assets of households with zero, one, two, three or four measures, equalling on average US$600, US$850, US$2600, US$4,800, and US$5,400 by the end of the running period, and while evaluating households' start income, start assets and end assets (Table 4.2). There appears to be a significant difference (one,-sided t-test, alpha = 0.05) between the start income of all groups and between the end assets of all groups of Table 4.2. This shows that existing inequalities between households are exacerbated over time as a result of a path-dependent Matthew effect. The ability to adopt measures at an early stage reduces the vulnerability to droughts and thereby increases financial capacity to further increase resilience. Conversely, a lack of capacity to adapt translates to a progressively diminishing lack of capacity, a poverty trap.

*Table 4.2. Economic profile households.*

| **Measures adopted at simulation end** | start income | start assets | end assets |
|---|---|---|---|
| no measures | 1232 | 358 | 602 |
| Mulch | 1344 | 369 | 1250 |
| Fanya Juu | 1300 | 371 | 1071 |
| Well | 1564 | 390 | 5274 |
| Drip Irrigation | 1599 | 381 | 6536 |
| *Average* | *1295* | *366* | *1146* |

Figure 4.8 depicts the amount of food aid (US$) required to ensure food security per 1,000 households as modelled through ADOPT. Food aid was calculated as the sum of US$ required for all households to fulfil their food requirements, accounting for a variable food price. Thus, ADOPT can be used to calculate the average annual costs of droughts (i.e., the direct economic loss for a government assuming it provides full food aid to all households in need; see Table 3). In the BAU, bounded rational, and economic rational scenarios, the annual average losses caused by droughts (costs to governments) equalled US$ 71.1k, 48.0k, and 19.9k per 1,000 households, respectively, on an annual basis. These estimates are a result of food supply shortages in the study area caused by droughts as well as the limited possibilities for households to buy food because of extreme poverty. Differences were significant between the three scenarios, as the bounded rational scenario estimated needs 32.5% lower and the economic rational scenario estimated needs 72.0% lower than the business as usual scenario where no additional adaptation happened. There is a clear decrease in drought vulnerability in the economic rational scenario, with emergency needs reduced to almost zero. The high total production, due to the large amount of households which adopted irrigation techniques, results in ample food supply even in times of drought. This is not the case in the BAU and bounded rational scenario, where the regional food supply is insufficient during drought years.

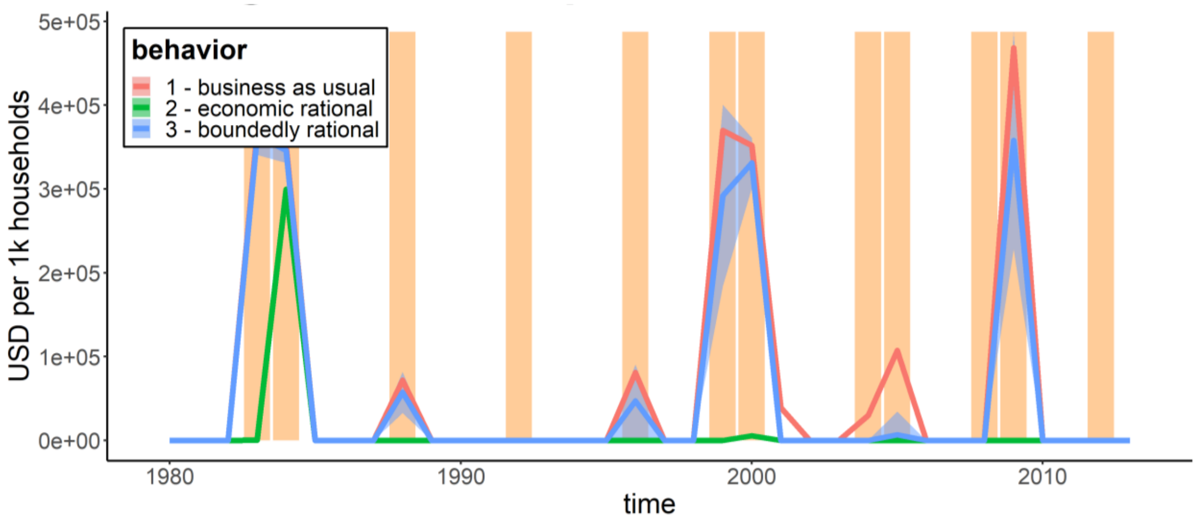


*Figure 4.8. Food aid required per thousand households. Food aid was calculated as the cumulative amount of food shortage of all individual households multiplied by the maize price, accounting for a variable food price. Variability over time is visualized for three behavioural scenarios: economic rational (EUT), bounded rational (PMT), and no adaptation decisions (BAU). Drought years (SPEI value in crop season $< -1$) are visualized as vertical orange bars. The shaded blue area shows the variance among 50 bounded rational model runs, a result of the variety in weights of the PMT factors.*

*Table 4.3. Average annual simulated cost of droughts (US$ per thousand households).*

| Behavioural scenario | Estimated average annual aid need (USD) assuming | |
|---|---|---|
| | *heterogeneous set of households* | *homogeneous set of households* |
| Business-as-usual scenario | 71.4K | 34.7K |
| Bounded rational scenario | 56.9K | 27.6K |
| Economic rational scenario | 16.0K | 7.7K |

Furthermore, Table 4.3 shows the ADOPT estimation of the average annual cost of droughts for a government (US$ per thousand households) for providing all the food needs for households in food insecurity in case of a heterogeneous and homogeneous set of households. When the total harvest in the study area was assumed to be equally distributed among all households and all households could afford to buy their food need equivalents, average annual food aid needs over this period would be US$ 34.7k, 27.6k, and 7.7k USD for the BAU, bounded rational decision, and economic rational decision scenarios, respectively. This method of calculating aid needs, through excluding the agent-based approach, yielded underestimations of food aid needs by 51% as compared to the respective heterogeneous, multi-agent-based estimations. This showcases the added value of evaluating risks and the needs for food aid on an individual household basis.

Moreover, comparing food aid numbers for the severe droughts of 1984, 2000, and 2009, the influence of the different adaptive behaviours on the drought disaster impact can be observed. In the '83–'84 drought, a food aid peak of US$ 745k could be observed in the bounded rational scenario, whereas BAU assumptions resulted in an estimate of US$ 758k and the economic rational scenario yielded an estimate of only US$ 256k. This is 66% less than the BAU scenario, which means the sudden adoption of drought adaptation measures in the economic rational scenario is immediately effective in disaster risk reduction. During the 1999–2001 drought, the BAU, bounded rational, and economic rational scenarios exhibited emergency aid needs of US$ 820k, US$ 428k, and US$ 0, respectively, and the 2009 drought ends up with emergency aid needs of US$ 490k, US$ 205k, and US$ 0 in the BAU, bounded rational and economic rational scenarios, respectively. For the bounded rational scenario, this translates to a reduction in the disaster impact of 47.8% in 2000 and 58.1% in 2009, as compared to the BAU conditions. For the economic rational scenario, this translates to a full reduction in the disaster impact, resilience is achieved. These vast differences reveal the large influence of adaptation, and the assumptions about the dynamics of it, on drought disaster risk assessments.

## 4. Discussion

In this contribution, we present a socio-hydrological, agent-based model, ADOPT, which integrates the crop model AquacropOS with a behavioural model to apply different decision theories. The ADOPT model framework is capable to be calibrated for any drought-prone area dominated by smallholder farmers. Here, ADOPT is deployed to model subsistence farmers in Kitui, Kenya. Our model highlights the importance of accounting for the behaviour of individuals and households who, through adaptive decision-making, influence the drought disaster risk they are subjected to. A failure to account for behaviour in drought disaster risk models leads to an underestimation of required food aid. While results should be interpreted with care given the assumptions and simplifications made, the use of various behavioural models show the range of possible behavioural effects as they emerge from an integrated social-hydrological feedback. The ADOPT model is thus useful as a first step in integrating adaptive behaviour in drought disaster risk modelling, while more work is required to parameterize the complex behavioural rules needed to accurately predict future drought disaster risk scenarios. The following paragraphs discuss the differences between the applied model scenarios, model calibration, and validation and sensitivity analysis.

### 4.1. Model Scenarios

Insights into the co-evolution of human adaptation and drought disaster risk are vital to the assessment of future drought disaster risk and the development of any disaster risk reduction strategy. However, the assumptions about adaptive behaviour, implemented through the use of different decision theories, highly influence the estimations of future risk (De Koning, 2019). Through comparing complex behavioural dynamics against a BAU and an economic rational scenario, we were able to show the relative influence of empirical adaptive behaviour (and its uncertainty) on general food security and poverty indicators in a Kenya-based case study.

While economically rational farmers implement affordable adaptation measures at a fast rate, thereby increasing their maize yield, the adoption of drought adaptation measures occurs more gradually under bounded rational conditions. This slower uptake is influenced by the occurrence of droughts, which have a negative effect on the financial assets of households, thus reducing their coping appraisal. However, the frequency of droughts in the study area keeps their risk appraisal rather high. The intention to adopt for bounded rational farmers is therefore almost never zero, which is also confirmed by empirical evidence (Chapter 3). The bounded rational scenario leads to more realistic estimations of the adoption of drought adaptation measures, except for the estimations on mulching. This labour-intensive technique, which also limits the feeding of unharvested crop residue to livestock, is potentially undervalued in the model.

Furthermore, the ADOPT results clearly shows the ability to simulate the dynamics of a poverty trap: smallholder farmers can be impoverished due to drought shocks, disabling them from adopting drought adaptation measures, and consecutive droughts can be a reason for remaining poor and increasing food insecurity. The adoption of drought adaptation measures by bounded rational households reduced drought-related economic loss by 30% compared with the BAU scenario; economic rational households exhibited a reduction of 78% compared with BAU. From this estimation, it is evident that the choice of adaptation theory matters when estimating risk.

### 4.2. Model Validation

The validation of a complex behavioural model is challenging because of unique feedbacks and a lack of empirical data (Claessens et al., 2012; Brown et al., 2017). Hence, the research in this Chapter must be seen as a sensitivity analysis for assessing the influence of behavioural dynamics on drought disaster risk rather than an attempt to reproduce the correct absolute estimates on yield and risk. However, to derive realistic results, we followed some of the recommendations described by Cirillo and Gallegati (2012) to establish the model and used observed data to initialize and calibrate ADOPT. For example, (1) we used reanalysis climate data from CHIRPS (Funk et al., 2015a); (2) AquacropOS is specifically designed for semi-arid areas, such as Eastern Africa (Vanuytrecht et al., 2014) and was calibrated to the specific geographical characteristics of Kenya (based on Ngetich et al., 2012); and (3) we undertook a survey in the region (Chapter 3) to obtain the empirical socioeconomic parameters to initialize ADOPT. While this data was complemented with existing household survey data from 2000, 2004, 2007, 2010 (Tegemeo Institute, 2000, 2004, 2007, 2010), it remains a limitation to represent 30 years of model dynamics by data from a few snapshots in time

The calibration of AquacropOS was done based on research done by other authors, who calibrated AquacropOS for this region. A dedicated experiment of crop yield under different weather, soil and management circumstances would have decreased this uncertainty, but this was beyond the scope of this research. However, A validation of ADOPT model results against historical average maize yields showed that simulated yields of 0.6 t/ha (±0.25) matched the peaks and averages for the Kitui region of 0.6 t/ha (±0.4) (e.g., Hansen and Indeje, 2004; Barron and Okwach, 2005; Aylward et al., 2015; Mumo et al., 2018; Ayugi et al., 2020). Furthermore, the simulated range of people in food insecurity and people in poverty fitted the observed ranges and variance over time: Ifejika et al. (2008) reported that 91% of rural households experienced food insecurity during the 1999–2000 drought, which is similar to the modelled peak using ADOPT. Peaks in poverty in 2000, around 2004, and 2009–2010 were also observed by (Nyariki and Wiggins, 1997; Johnson and Wambile, 2011; Oluoko-Odingo, 2011).

### 4.3. Sensitivity Analysis

A sensitivity analysis was performed to evaluate the effect of assumptions in PMT on the uptake of adaptive measures and related effects on yields. Sensitivities were visualized by shaded uncertainty ranges in the graphs found in section Results. Changing the initialization values of the households did not significantly affect the average maize harvest nor average aid needed over time. When varying the share of households receiving extension services between 10 and 90%, estimates on average household maize harvest varied between 971 and 1,000 kg per year, respectively. When varying the PMT weights $\alpha$ and $\beta$, changing the relative importance of risk appraisal and coping appraisal (subsection 2.2.3, Adaptation Intention Equation 2), between 66 and 33%, the resulting household maize harvest estimates ranged between 993 and 987 kg per year, respectively. Varying the weights in the coping appraisal equation, changing the relative importance of self-efficacy, adaptation-efficacy and adaptation costs ($\gamma$, $\delta$, and $\varepsilon$, subsection Simulating the Adaptive Behaviour of Subsistence Farmers, Equation 4) between 25 and 50%, household maize harvest estimates ranged between 982 kg (when adaptation costs have a weight of 50%) and 1,003 kg (when adaptation efficacy has a weight of 50%).

The estimated average food aid needs over the 30 years of simulations varied between US$ 61.544–53.584 when changing the share of households receiving extension services between 10 and 90%; between US$ 57.152 and 57.391 when changing the relative influence of risk perception from 66 to 33% (Equation 2); and between US$ 54.360 and 58.955 when altering the weights of self-efficacy, adaptation efficacy, and adaptation costs (Equation 4). It is clear that the weights used to estimate the intention to adopt did influence the final outcome: Increasing the influence risk perception or giving more importance to adaptation efficacy increased the average maize harvest, while it decreased the average aid needed. assumptions about an external factor—the extension services—are shown to have a larger impact on the results: raising the share of households receiving this form of training increased the average maize harvest and reduced the aid needed more than any of the changes in weight of the PMT factors. This indicates that increasing the frequency of extension services in addition to raising households' risk perception or thrust in the adaptive efficacy, can positively influence the adoption rate hence decrease drought disaster risk. However, the variability introduced by the different behavioural scenarios, and thus the assumptions of BAU (static vulnerability) and economic rational behaviour (full information), are highlighted as the largest influencing factors on the results, proving the importance of correctly including human adaptive behaviour in drought disaster risk models.

### 4.4. Scope for Further Research

Not all possible adaptive behaviours could be included in our modelling setup. For example, Kenyan households often cope with droughts by increasing livestock sales, serving as a buffer against absolute poverty in times of failed harvests (Few et al., 2006; Ifejika, 2010; Oluoko-Odingo, 2011). In ADOPT, livestock trade is not included, explaining the relatively high peaks in poverty during droughts. Furthermore, the potential application of different drought tolerant seeds and/or varieties can be included, which would require detailed information about the variety's agronomic sensitivity to water stress. Another way to reduce modelling uncertainty in future applications is including a changing planting date based on weather predictions, as is reported on the field (Chapter 4) but currently impossible in AquacropOS. Future research could work to include these drought adaptation strategies to create a broader picture of smallholder adaptive behaviour in the face of droughts in semi-arid Kenya. Besides, while now only precipitation was seen as a source of water, a follow up study could couple the ADOPT model to a spatially distributed hydrological model and investigate the influence of water abstractions on the water availability in rivers or groundwater. As such, proximity to the river and other geographic drivers for adaptation can be included.

## 5. Concluding Remarks

Smallholder farms in Africa are increasingly affected by droughts, which are expected to intensify with climate change and socioeconomic trends. However, while these farmers have a critical role regarding efficient use of water and the production of food (e.g., UN Water Action decade 2018–2028, UN Decade of Family Farming 2019–2029), their individual decision-making is often neglected in drought disaster risk assessments (Moran et al., 2007). Disentangling the role of emergent adaptation decisions improves the understanding of current and future drought disaster risk (Aerts et al., 2018). Aiming to address this modelling gap, we developed a socio-hydrological, agent-based drought disaster risk model, ADOPT, which couples a physically based crop growth model (AquacropOS) with an adaptation decision model. Designed using socio-hydrological and agent-based modelling approaches, ADOPT simulates the two-way interaction between rain-fed agricultural production variability and the emergence of drought adaptation measures. Initialized with new survey data from households in central Kitui, the model showcased its ability to analyse historical yield losses caused by droughts, the impact of these losses on smallholder farmers, and the adaptive response of farmers to droughts. Three different behavioural scenarios were tested: one where households could not adopt new adaptation measures (business as usual), one where they behaved economically rationally (following the expected utility theory), and a more realistic approach where they followed a bounded rational logic (using the protection motivation theory).

Results highlight that current estimations of drought disaster risk and the need for emergency food aid can be improved using an agent-based approach. Besides, we show that working with an "average household"—thus not accounting for the existing inequality—underestimates the number of aid needs. Furthermore, our study finds that assumptions about the adaptive behaviour of households highly influence drought disaster risk estimations. ADOPT simulations show how the dynamics of adaptive decision-making, which emerge from interactions between individual agents and their environments, influence yields and other risk indicators. Accounting for bounded rational decision-making, a significant difference in annual average yield loss could be seen in comparison to the more conventional BAU or economic rational scenarios. Moreover, the magnitudes estimated while assuming bounded rational households were found to be closest to observed data. By incorporating the effects of bounded rational adaptive behaviour, we conclude that ADOPT is better able to better simulate drought disaster risk over time than classic assumptions with respect to adaptation behaviour.

Following recent research in socio-hydrology, the ADOPT model can be seen as an experimental setup for improving our understanding of the socioeconomic and environmental factors that influence drought disaster risk and management over time. While now, it shows how different drivers steer household's adaptation decisions and how these affects their personal and community drought disaster risk, it could also be used to assess future drought disaster risk and to evaluate the effect(iveness) of specific NGO or governmental actions and policy. The ADOPT framework can be applied to study food insecurity in other case studies, or used to answer questions about other adaptation strategies, aiming at improved livelihoods and reduced drought disaster risk. Besides, it can be employed to study the effect of certain governmental policies on households' drought disaster risk behaviour or, coupled to a spatially distributed hydrological model, it can enable us to study trade-offs between drought disaster risk for different water users up- and downstream catchments. This work represents an important next step in drought disaster risk modelling and toward enhanced agricultural water management.

# CHAPTER 5:

## EDUCATION, FINANCIAL AID AND AWARENESS CAN REDUCE SMALLHOLDER FARMERS' VULNERABILITY TO DROUGHT UNDER CLIMATE CHANGE

### *AN ADOPT MODEL APPLICATION*

*This Chapter is published as:*

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## Samenvatting

Analyses van toekomstige gevolgen van droogte in de landbouw vereisen een multidisciplinaire aanpak waarin zowel de menselijke als de milieudynamiek worden bestudeerd. In dit hoofdstuk hebben we het agent-gebaseerde droogterisicomodel ADOPT toegepast om het effect van verschillende droogterisico-beperkende interventies op kleine agrariërs in de Keniaanse rurale gebieden te beoordelen. Bovendien werd de robuustheid van deze droogte-interventies onder verschillende klimaatveranderingsscenario's geëvalueerd. Het ADOPT model simuleert waterbeheerbeslissingen van kleine agrariërs, en evalueert de voedselonzekerheid, armoede en noodhulpbehoeften van huishoudens als gevolg van droogterampen. Het model is gebaseerd op uitgebreide veldonderzoeken en interviews waaruit beslissingsregels zijn gedistilleerd op basis van theorieën over begrensd rationeel gedrag.

De modelresultaten suggereren dat aangepaste trainingen voor agrariërs de toepassing van goedkope, nieuwere droogtemaatregelen vergroten, terwijl kredietregelingen nuttig zijn voor kosteneffectieve maar dure droogtemaatregelen, en financiële transfers vóór de droogte de minst vermogende huishoudens in staat stellen goedkope welbekende maatregelen te nemen. Systemen voor vroegtijdige waarschuwing blijken doeltreffender in klimaatscenario's waar droogte minder frequent voorkomt. Het tegelijkertijd toepassen van deze vier beleidsacties heeft een wederzijds versterkend effect: het zorgt voor een sterke toename van droogtemaatregelen onder agrariërs en leidt tot minder voedselonzekerheid, minder armoede en een drastisch lagere behoefte aan noodhulp, zelfs onder warmere en drogere klimaatomstandigheden. Deze niet-lineaire synergiën wijzen erop dat een holistisch perspectief nodig is om de weerbaarheid van kleine agrariërs in de droge Keniaanse gebieden te ondersteunen.

## Summary

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

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

## 1. Introduction

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

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

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

Here we present how an agent-based drought risk adaptation model, ADOPT (designed in Wens et al 2020), can increase our understanding of the effect of drought policies on community-scale drought risk for smallholder farmers in Kenya's drylands. The design of ADOPT as an agent-based drought risk adaptation model is described in Wens et al., 2020. Moreover, Wens et al. (2021)

detail the empirical data on past adaptive behaviour (used to calibrate the model), as well as empirical data on adaptation intentions that can be used to compare with the model outputs.

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

## 2. Case study description

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

In Kenya, 75% of the country's maize is produced by smallholder farms. Maize is grown in the two rainy seasons, with the aim to meet household food needs (subsistence farming) (Erenstein, Kassie, & Mwangi, 2011; Erenstein, Kassie, Langyintuo, et al., 2011; Speranza et al., 2008). While during the long rainy season (March-April-May) multiple crops are planted, the short rainy season (October-November-December) is considered the main growing season for maize in the region (Rao et al., 2011). Reported smallholder maize yields often do not exceed 0.7 ton/ha. However, with optimal soil water management, yields can elevate to 1.3 ton/ha in the semi-arid medium potential maize growing zone in south-eastern Kenya (Omoyo et al., 2015). Few farmers use pesticides, improved seeds or other adaptation strategies (Tongruksawattana & Wainaina, 2019) .

In Kitui, Makueni and Machakos, the most preferred seed-variety is the high yielding but less drought resistant Kikamba/Kinyaya variety (120 growing days) with a potential yield of only 1.1 tons per hectare (Speranza, 2010; Recha et al., 2012). Trend analysis (1994-2008) shows that yields are declining due to the increasing pace of recurring droughts (Nyandiko, 2014). Over 97% of the smallholder farmers in this area grow maize, mainly for own consumption or local markets (Brooks et al., 2009; Kariuki, 2016; Nyariki & Wiggins, 1997). It is the main staple food, providing more than a third of the caloric intake, and is also the primary ingredient used in animal feeds in Kenya (Adamtey et al., 2016; FAO, 2008). . Only about 20% of the farmers are able to sell their excess crops, while 66% have to buy maize to complement their own production (Muyanga, 2004).

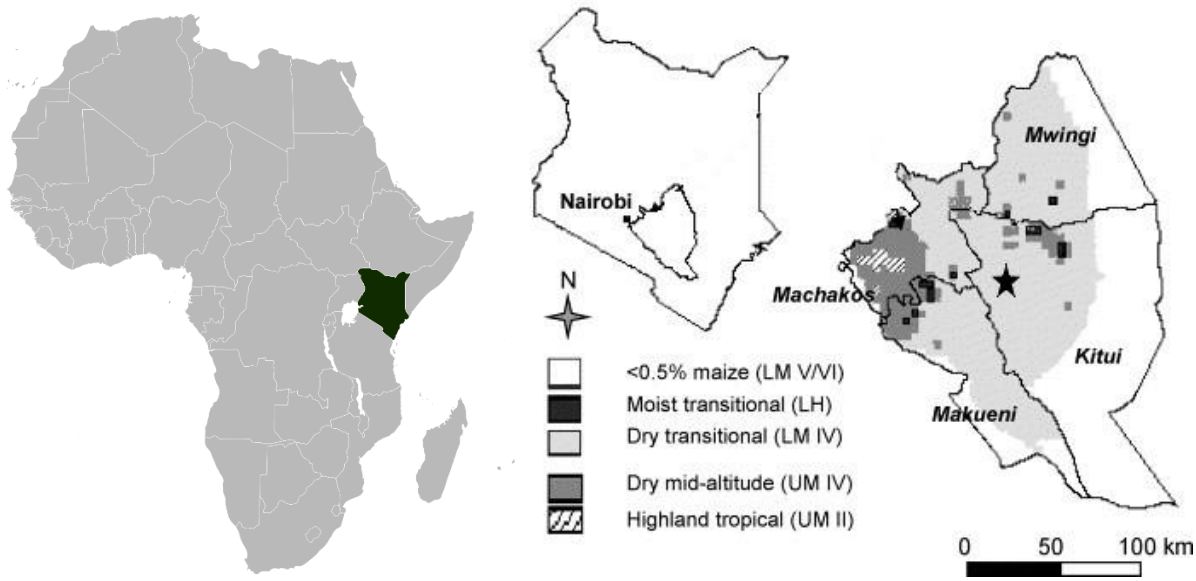


*Figure 5.1: Study area: dry transitional maize agro-ecological zone (right) located in South-Eastern Kenya (centre) in the Horn of Africa (left). Area where the survey data (Wens 2021) is collected is indicated with a star on the right map. Map adjusted from Barron and Okwach (Barron & Okwach, 2005)*

## 3. Model and scenario description

ADOPT (fig. 2, Wens et al 2020, ODD+D (Overview, Design concept, Details + Decision) protocol in Appendix 5A) is an agent-based model that links a crop production module to a behavioural module evaluating the two-way feedback between drought impacts and drought adaptation decisions. ADOPT was parameterized with information from expert interviews, a farm household survey with 260 households including a semi-structured questionnaire executed in the Kitui Region, Kenya (Wens et al. 2021). Moreover, a discrete choice experiment (a quantitative method to elicit preferences from participants without directly asking them to state their preferred options) was executed to get information on changes in adaptation intentions under future top-down DRR interventions (Wens et al. 2021). This empirical dataset feeds the decision rules in ADOPT describing farm households' adaptive behaviour in the face of changing environmental conditions (drought events), social networks(actions of neighbouring farmers), and top-down interventions (drought management policies).

In ADOPT, crop production is modelled using AquacropOS (Foster & Brozović, 2018), simulating crop growth on a daily basis and producing crop yield values at harvest time twice per year. Calibrated for the Kenyan dryland conditions (Ngetich et al., 2012; Wamari et al., 2007), AquacropOS considers the current water management of the farm (i.e., the applied drought adaptation measures) and yields vary with weather conditions. The adaptive behaviour of the farm households (agents) is modelled based on the Protection Motivation theory (PMT, Rogers 1975). This theory was derived as promising in an earlier study (Wens et al, 2020) and includes multiple relevant factors that drive the observed behaviour of farm households (Wens et al 2021). In this application of ADOPT, the model was run over 30 historical years as baseline followed by 30 years of future scenarios (combinations of policy and climate changes; the start of these changes is indicated as "year 0"). Through a sensitivity analysis, both the average effect of individual adaptation decisions and its endogenous model variability are analysed (similar to Wens et al 2020). We used 12 different initialisations per scenario to include variations in model initialisation, the stochasticity that determines the individual adaptation decisions, and the relative weights of factors influencing behaviour (See 3.1).

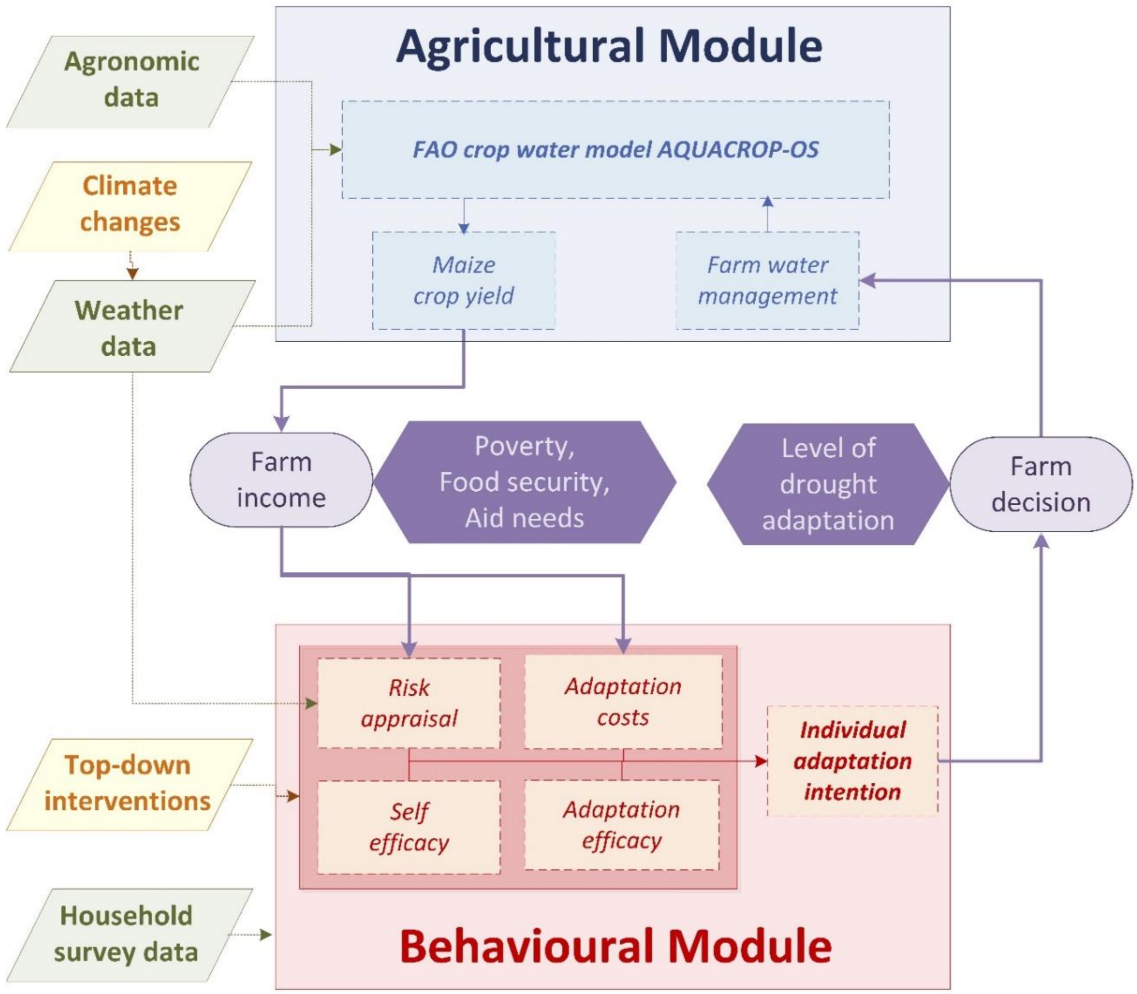


*Fig. 5.2: ADOPT model overview, adjusted from Chapter 5. Description of the model in ODD+D in Supplementary.*

### 3.1. Individual adaptive behaviour in ADOPT

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

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

### 3.2. Drought disaster risk indicators in ADOPT

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

### 3.3. Climate change scenarios

Multiple climate change scenarios – all accounting for increased atmospheric carbon dioxide levels - were tested: a rising temperature of 10%, a drying trend of 15%, a wetting trend of 15%, and various combinations of these. The warming and drying trends were based on a continuation of the trends observed in the last 30 years of daily NCEP temperature (Kalnay et al., 1996) and CHIRPS precipitation (Funk et al., 2015) data (authors' calculations; similar trends found in (Gebrechorkos et al., 2020)). The wetting trend was inspired by the projections from most climate change models which predict an increase in precipitation in the long rain season – a phenomenon known as the 'East African Climate Paradox'(Gebrechorkos et al., 2019; Lyon & Vigaud, 2017; Niang et al., 2015). The no change scenario was a repetition of the baseline period, without changing precipitation or temperature hence only elevated carbon dioxide levels. Reference evaporation was calculated for each scenario using the Penman-Monteith model and thus influenced by temperature changes (Allen, 2005; Droogers & Allen, 2002).

*Table 5.1: Average (daily temperature, annual precipitation) weather conditions (1980-2010) in ADOPT*

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

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

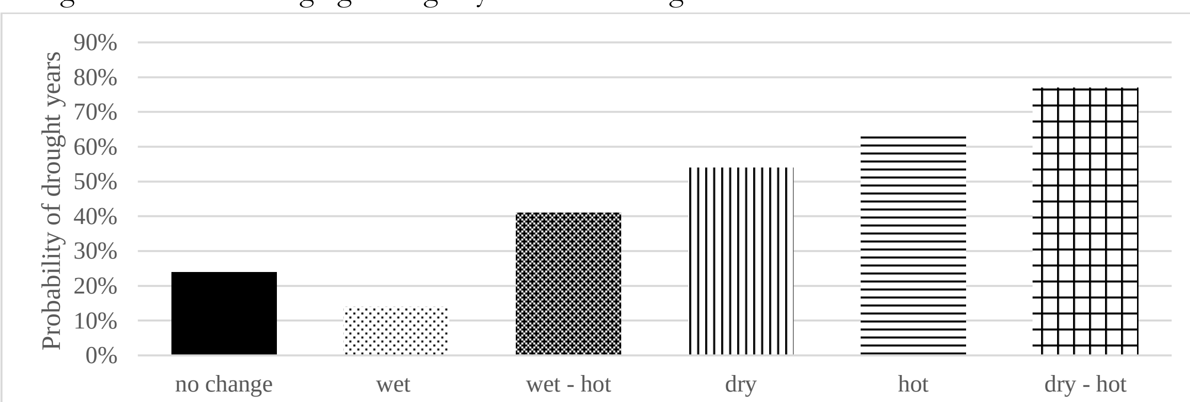


*Fig. 5.3: Probability of having a year with three or more consecutive months under a SPEI < -1, for the climate change scenarios.*

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

### 3.4. Drought disaster risk reduction intervention scenarios

Four policy interventions are evaluated, chosen based on key informant interviews (chapter 4) and current national policy documents. Kenya Vision 2030 for the ASAL promotes drought management through extension services and aims to increase access to financial services such as affordable credit schemes (Government of Kenya, 2012; Kenya, 2016). Besides, building on the Ending Drought Emergencies plan, the National Drought Management Authority prioritizes the customization, improvement and dissemination of drought early warning systems. It aims to establish trigger levels for ex-ante cash transfer so as to upscale drought risk financing (Government of the Republic of Kenya, 2013; National Drought Management Authority, 2015; Republic of Kenya, 2017). Improved extension services tailored to the changing needs of farm households (Muyanga & Jayne, 2006), a better early warning system with longer lead times (Deltares, 2012; van Eeuwijk, n.d.), ex-ante cash transfers to the most vulnerable when a drought is expected (Guimarães Nobre et al., 2019) and access to credit-markets (Berger et al., 2017; Fan et al., 2013) are all assumed to increase farmers' intention to adopt new measures.

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

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

I. Reactive policy intervention "supporting drought recovery": No (new, pro-active) interventions are implemented. Only emergency aid (standard in the ADOPT model to avoid households to die) is given to farmers who lost their livelihoods after drought disasters; this food aid is distributed to farmers who are on the verge of poverty to avoid famine.

II. Pro-active policy intervention plan "preparing for drought disasters": Improved early warnings are sent out each season if a drought is expected. This is assumed to raise all farmers' risk appraisal with 20%. Ex-ante cash transfers are given to all smallholder farmers (those without income off-farm and without commercialisation) to strengthen resilience in the face of a drought. This is done when severe and extreme droughts (SPEI <-1, and <-1.5) are expected that could lead to crop yield lower than respectively 500kg/ha and 300kg/ha. Money equivalent to the food insecurity following these yields is paid out to farmers with low external income sources. Moreover, like in the reactive government scenario, emergency aid is given to farmers who need it.

III. Prospective policy intervention plan (UNDRR 2021) "mitigating (future) drought disasters": Credit rates are lowered so that it is affordable to people to take a loan for adaptation measures, at an interest rate of 2% and a pay-back period of five years. Besides, emergency services are provided in the form of frequent trainings given in communities with poor practices to improve their capacity related to drought adaptation practices for agriculture. Moreover, like in the proactive government scenario, an improved early warnings system is set up and ex-ante cash transfer is given. Lastly, emergency aid is given to farmers who need it.

## 4. Results

### 4.1. Maize yield under different adaptation measures and future climate scenarios

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

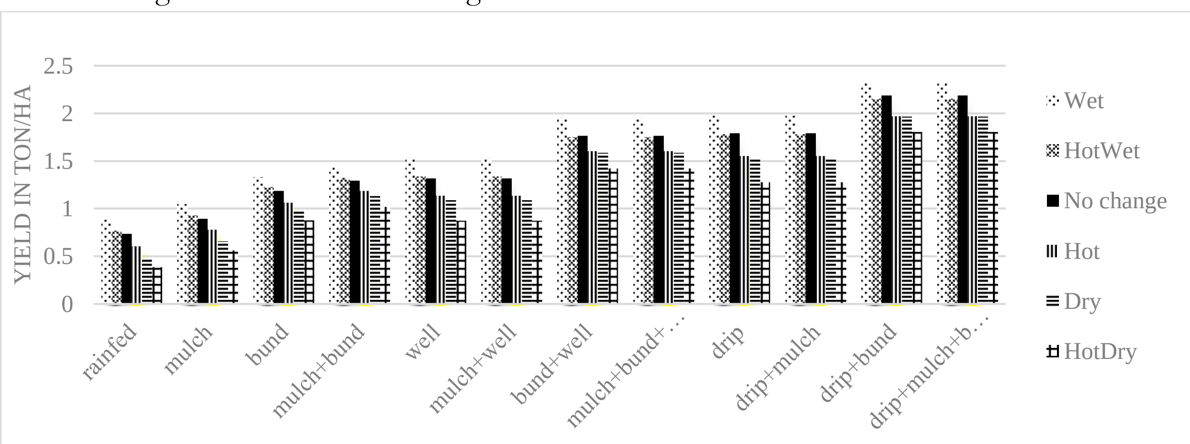


*Fig. 5.4: Average maize yield under different agricultural water management conditions and different future climate scenarios.*

### 4.1. 4.2 The adoption of adaptation measures over time

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

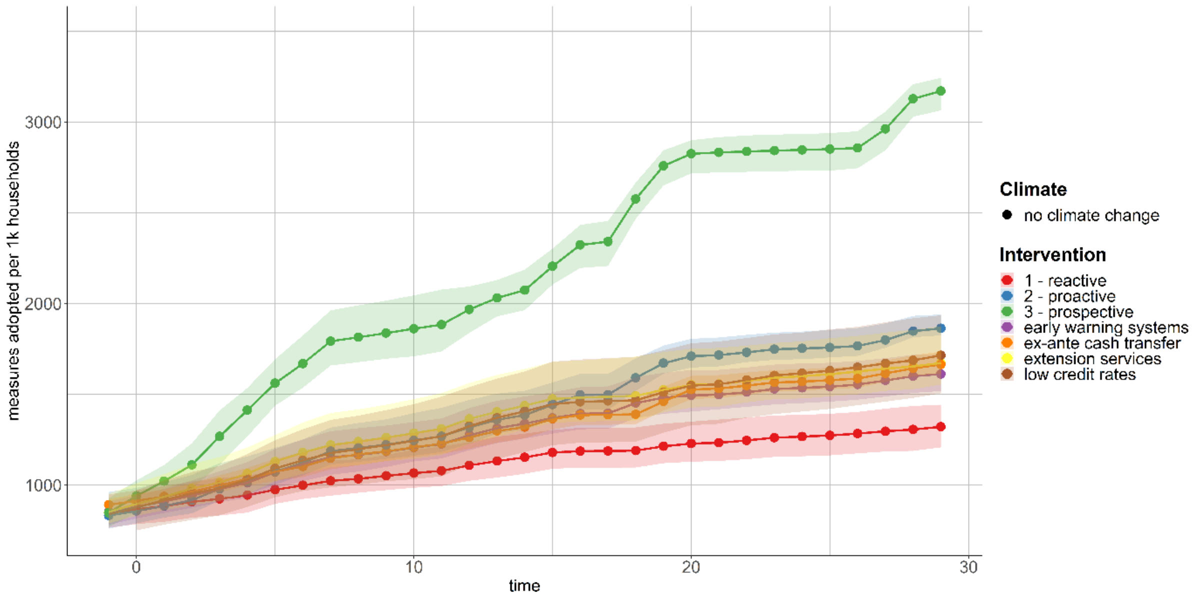


*Fig. 5.5: Total amount of measures adopted per 1000 initialized households under no climate change, averaged over all runs. The shaded area indicates the variation - uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households (sensitivity analysis). Year 0 initiates policy drought risk reduction interventions (indicated with different line colours).*

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

Overall, although the processes through which the interventions support households to adapt differ significantly, the differences in eventual adoption rate under the different interventions were small (they overlap in uncertainty interval). Also, the effect of climate change on the adoption rate (Figure 5A, Table 5B in Appendix) was rather small when evaluating the reactive (no intervention) scenario. However, with interventions, the climate change scenarios differed more.

When examining the effect of the three intervention scenarios (Figure 5B, table 5B in Appendix), it is clear that implementing multiple policies at once resulted in a stronger increase in adoption: a proactive and prospective intervention plan increased the adoption of different adaptation measures with respectively 40% and 140% more than under the "reactive, no climate change" scenario where no intervention takes place. Both a proactive and prospective approach increased the adoption of cheaper adaptation measures to close to 100% of the farm households. For more expensive measures, the proactive scenario showed to be less effective while the prospective scenario reached quite high adoption rates in the more extreme climate scenarios.

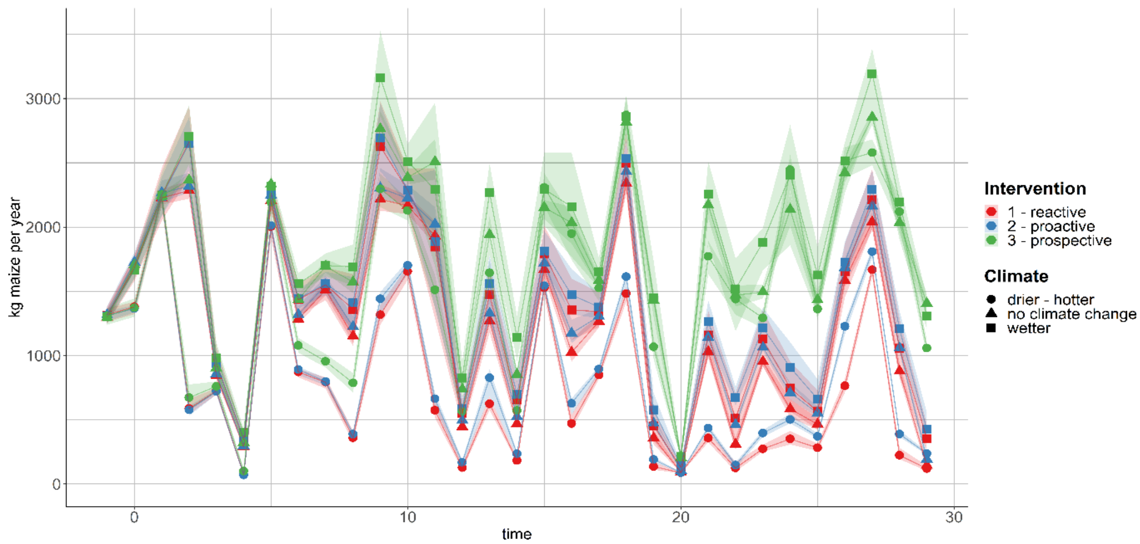


*Fig. 5.6: Household maize harvest (kg/year, sum of two growing seasons) over 30 'scenario years' under different climate change and policy intervention scenarios. The shaded area indicates the variation - uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households (sensitivity analysis)*

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 – with an increasing effect over the years (increasing difference in harvest between reactive and other scenarios, 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 by over 60% under dry-hot future conditions. Clearly, an increased uptake of measures under this intervention scenario would potentially offset a potentially harmful drying climate trend.

### 4.2. Drought risk dynamics under policy and climate change

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. It is important to remark that the different between the intervention scenarios and the reactive scenario is only clearly visible after more than 10 years under most future climate scenarios.

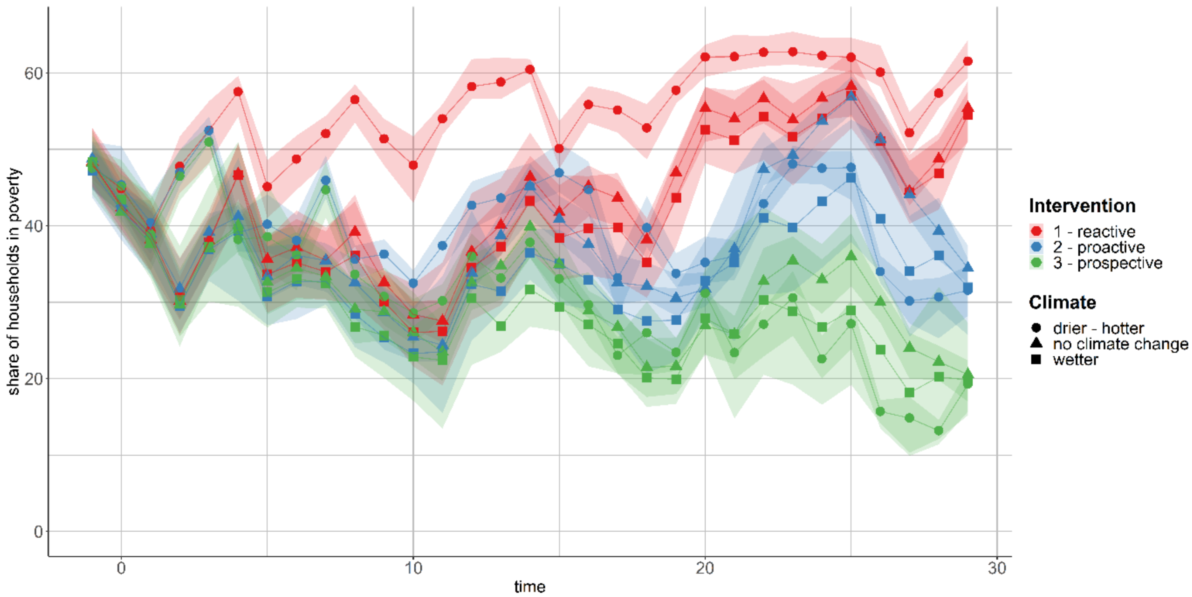


*Fig. 5.7: Share of households in poverty (earning under the 2USD/day income line, under different climate and policy intervention scenarios). The shaded area indicates the variation - uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households (sensitivity analysis).*

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

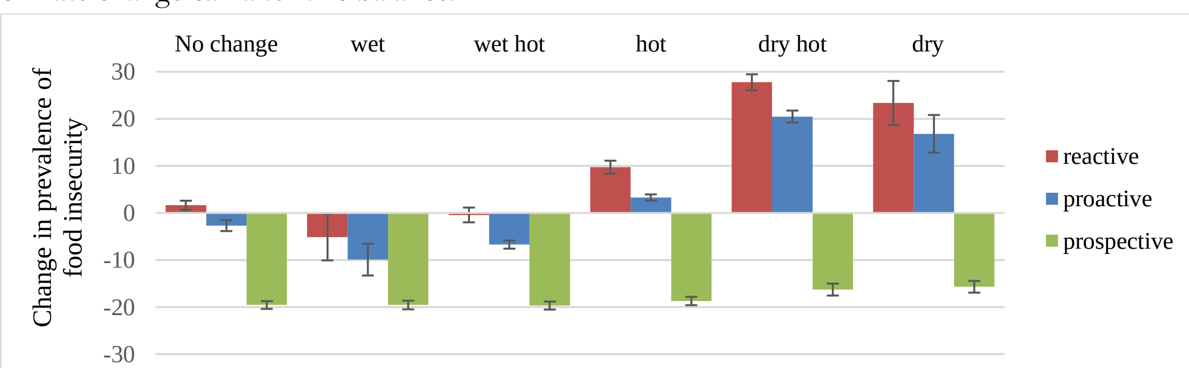


*Fig. 5.8: Absolute change (average and standard deviation introduced by sensitivity analysis - variation caused by different model initialisations and by different relative importance of the PMT factors on the decisions of households) in average share of households in food shortage of the 20 last years of scenario run, compared to the first 20 years of baseline run before "year 0", under different climate and policy intervention scenarios. ADOPT model output.*

Improving extension services or providing ex-ante cash transfers individually showed on average 7.5% more reduction in food insecurity than the reactive government scenario. Improved early warning systems showed on average - over all climate scenarios- an increased reduction of 4.5%. It should be kept in mind that ADOPT does not consider (illicit) coping activities in the face of droughts which can – if a drought warning is send out – allow households to avoid buying food at high market prices or to engage in other income-generating activities such as food stocking or charcoal burning (Eriksen et al., 2005). However, both of them might reduce the food security threat. Credit schemes at 2%, individually, lead to more than 8% reduction in food insecurity levels as compared to the reactive scenario; but even then, on average net food insecurity rates increase due to climate change. A proactive intervention resulted in a food insecurity rate which is 6 percent points lower than under the reactive scenario; but still showed increases in the prevalence of food insecurity under hotter and drier conditions. A prospective intervention, combining all four interventions, was able to consistently reduce the food insecurity levels over time, even under the dry-hot climate scenario. This scenario was able to counteract the increase in food insecurity, achieving a reduction of households in food shortage over time with on average 28% compared to the reactive scenario, all climate scenarios considered.

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

*Table 5.2: Change in aid needs (%) in 2030-2050 compared to 1980-2000 (average and standard deviation introduced by sensitivity analysis - variation caused by different model initialisations and by different relative importance of the PMT factors on the decisions of households) under different climate and policy intervention scenarios. ADOPT model output.*

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

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

## 5. Discussion

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

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

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

The proactive government scenario, "preparing for drought disasters" by improving early warning systems and supporting ex-ante cash transfers, has a larger effect on drought risk. However, this effect is not as much as the sum of the effect of the two interventions. In contrast, the prospective government scenario "mitigating drought disasters" by combining all four interventions, alleviates multiple barriers to adoption at once. This creates a significant, non-linear increase in adoption, matching the significant positive correlation between the preferences for extension, credit, early warning in Wens et al. 2021. Consequently, this scenario results in a clear growth in resilience of the farm households, shown in more stable income, lower poverty rates and less food insecurity. However, depending on the climate scenario applied, the effect of increased adoption due to a prospective interventions on household maize production, thus on food security and poverty, is only visible after a few years under drier conditions and after more than ten years under wetter conditions.

### 5.2. The robustness of drought risk reduction interventions under climate change

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

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

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

### 5.3. ADOPT as a dynamic drought risk adaptation model

In the past decade, the use of agent-based models (ABM) in *ex-post* and *ex-ante* evaluations of agricultural policies and agricultural climate mitigation has been progressively increasing (Huber et al., 2018; Kremmydas et al., 2018). A pioneer in agricultural ABM is Berger (2001) who couples economic and hydrologic components into a spatial multi-agent system. This is followed more recently by for example Berger and Troost (2011), Van Oel and Van Der Veen (2011), Mehryar et al. (2019) and Zagaria et al. (2021). The socio-hydrological, agent-based ADOPT model follows this trend in that it fully couples a biophysical model—AquacropOS—and a social decision model—simulating adaptation decisions using behavioural theories—through both impact and adaptation interactions.

The initial ADOPT model setup was created through interviews with stakeholders (Wens et al. 2020), and the adaptive behaviour is based on both existing economic – psychological theory and on empirical household data (Wens et al. 2021). The assumption of heterogeneous, bounded rational behaviour is addressed yet only by a few risk studies (e.g. Van Duinen et al. 2015, 2016; Hailegiorgis et al. 2018, Keshavarz and Karami 2016, and Pouladi et al. 2019). These studies have implemented empirically supported and complex behavioural theories in ABMs similarly to ADOPT (Schrieks et al. 2021; Jager, 2021; Taberna et al., 2020; Waldman et al., 2020).

ADOPT differs from these models, however, through its specific aim to evaluate households and community drought disaster risk beyond the number of measures adopted, crop yield, or water use. Rarely (except e.g., Dobbie et al 2018) do innovation diffusion ABM use socio-economic metrics to evaluate drought impacts over time – while such risk proxies are of great social relevance. As such, ADOPT evaluates the heterogeneous changes in drought risk for farm households, influenced by potential top-down drought disaster risk reduction (DRR) interventions. It does so through simulating their influence on individual bottom-up drought adaptation decisions by these farm households and their effect on socio-economic proxies for drought risk (poverty rate, food security and aid needs). To our knowledge, this is rather novel in the field of DRR and drought risk assessments.

### 5.4. Uncertainties in ADOPT and limitations in investigated measures and interventions

While yield data has been validated over the historical period (Wens et al. 2020), the model output cannot be used as a predicting tool. This would require more extensive validations for which, currently, data is not available. Such data would include longitudinal information on household vulnerability and adaptation choices from areas where certain policies are being implemented, or detailed data on aid needs for the case study area. The past average poverty and food insecurity rates matched observations (Wens et al. 2020). However, absolute amounts of emergency aid needs are sensitive to the averages and fluctuations of household assets which proved harder to verify. Besides, poverty and food insecurity depend also on external, food or labour market and other influences which might change towards the future. Moreover, the simulated climate scenarios are not entirely realistic (because variability changes are ignored and because the synthetic future data is created based on statistics rather than physical climate and weather system changes). Moreover, the East African Climate Paradox (Funk et al., 2021) creates its own set of challenges predicting future weather conditions in the study area.

Unavoidably, multiple possible smallholder adaptation measures are omitted in this study: many more agricultural water management measures, agronomic actions, and other options under the umbrella of climate-smart agriculture, exist. Besides, only four different policy interventions are evaluated while various other exists. Costs of these top-down interventions are unknown, making cost-benefit estimates regarding drought risk reduction strategies not possible for this study. Studying additional measures or interventions is possible using the ADOPT model but requires (the collection of) more data for parametrization and calibration.

Another future improvement to the model could be to directly sample the empirical household survey data (Wens et al 2020) to create a synthetic agent set. Now, the creation of agents (households) with different characteristics is drawn from distribution functions based on frequencies in the empirical data. Such one-to-one data-driven approach is similar to microsimulation and gaining popularity among ABMs (Hassan et al 2010). Lastly, the model application does assume no shifts in the underlying weather and decision-making processes. To avoid the effect of systemic changes and black swan effect, only 30 "future" years are modelled.

Because the model setup could not be fully validated, and scenarios do not provide a complete overview of all possibilities, this study does not claim to provide a prediction of the future for south-eastern Kenya. However, ADOPT is meant to – rather than forecast drought impact - increase understanding of the differentiated effect of adaptation policies: the relative differences in the risk indicators are informative for the comparison of these top-down interventions under different changes in temperature and precipitation. This study showcases the application of ADOPT as a decision support tool. It evaluates the robustness of a few, dedicatedly chosen policy interventions on farm household drought risk under climate scenarios that are deemed to be relevant for the specific area. Future research can use ADOPT to study the differentiated effect of these interventions on different types of households, in order to tailor strategies and target the right beneficiaries of government interventions. .

## 6. Conclusion

Top-down interventions, providing drought and adaptation information as well as supporting the capacity to act on the basis of this information, are needed to increase the resilience of smallholder farmers to current and future drought risk. However, to which extent these interventions will steer farmers' intention to adopt drought adaptation measures, hence how effective they are in reducing the farm household drought risk, often remains unknown. In this study, the agent-based drought risk adaptation model ADOPT is applied to evaluate the effect of potential future scenarios regarding climate change and policy interventions on agricultural drought risk in south-eastern Kenya. The smallholder farmers in this region face barriers to adopt drought adaptation measures such as mulching, Fanya Juu terraces, shallow wells, and drip irrigation, to stabilize production and income.

ADOPT simulates their adaptive behaviour, influenced by drought occurrences under changing climate conditions. Adaptive behaviour is also influenced by top-down drought risk reduction interventions such as the introduction of ex-ante cash transfers, affordable credit schemes, improved early warning systems and tailored extension services. We demonstrate that the investigated interventions all increase the uptake of adaptation measures as compared to the reactive scenario under no climate change (business-as-usual). Extension services (+27% uptake) multiply adaptation knowledge and thus increase self-efficacy among the smallholders, which raises the adoption of less popular drought adaptation measures. Accessible credit schemes (+30% uptake), alleviating a financial barrier, are effective especially for more expensive drought adaptation measures. Early warning systems (+22% uptake), creating risk awareness, are more effective in climate scenarios with less frequent drought. Ex-ante cash transfers (+25% uptake) allow the least endowed households to climb out of the poverty trap by adopting low-cost drought adaptation measures and thus reducing future shocks. The effect of climate change on the adoption of adaptation measures is limited.

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

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

## Appendix Chapter 5

*Adoption rates of adaptation measures*

*Table 5A Adoption ratio (in share of population) at run year 30 under different climate and intervention scenarios. Note that the model showed an adoption rate of 25% for mulch, 70% for Fanya Juu, 9% for well and X% for irrigation at run year 0 (start of climate change and policy scenarios) .*

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

*Table 5B Difference in adoption RATIO (in share of population) under different climate and intervention scenarios compared to the reactive government scenario under no climate change (the BAU scenario).*

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

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

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

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

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

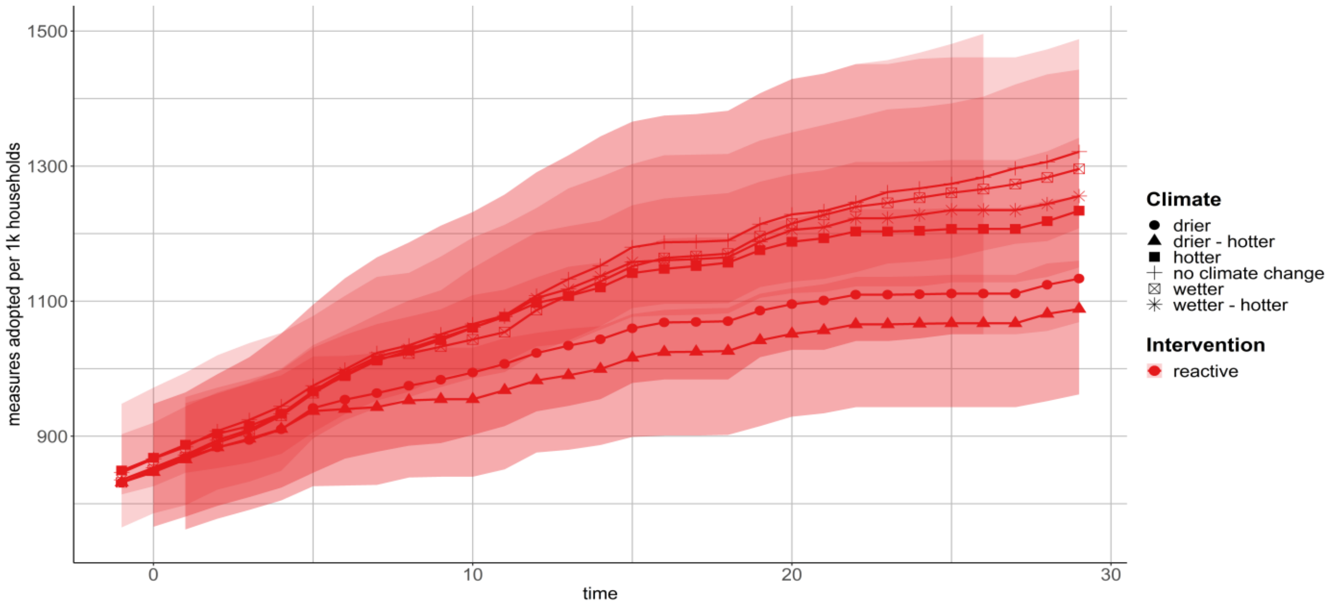


*Figure 5A: Total amount of measures adopted per 1000 initialized households under the reactive scenario, averaged over all runs. The shaded area indicates the uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households. Year 0 initiates policy drought risk reduction interventions (indicated with different line colours).*

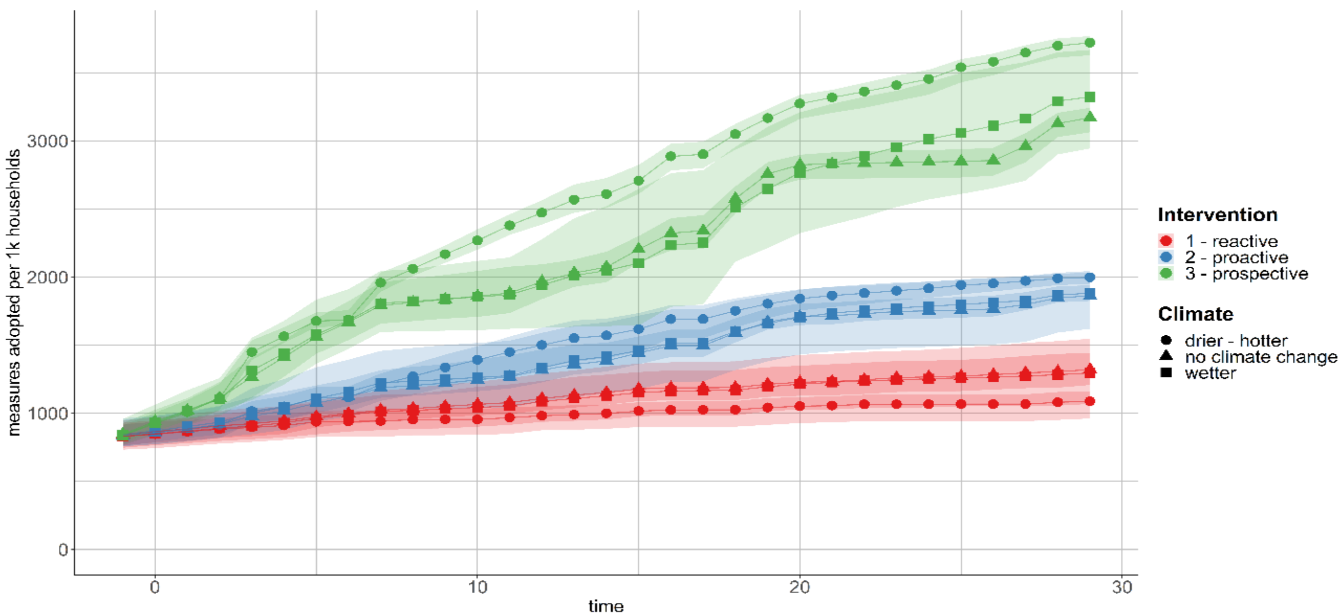


*Figure 5B: Total amount of measures adopted per 1000 initialized households under the three intervention scenarios and three climate change scenarios, averaged over all runs. The shaded area indicates the uncertainty introduced by different model initialisations and by different relative importance of the PMT factors on the decisions of households. Year 0 initiates policy drought risk reduction interventions (indicated with different line colours).*

# CHAPTER 6:

## CAPTURING ADAPTATION DYNAMICS IN DISASTER RISK MODELS

## *A SYNTHESIS TO THIS THESIS*

***"Through explicitly including the adaptive behaviour of smallholder farmers, including their interactions with each other and their agro-hydrological context, the dynamics of agricultural drought disaster risk under socio-economic, policy and climate change can be estimated"***

\- *Conclusion of this PhD dissertation* (Marthe Wens, 2022)

## 1. Research findings

In this thesis, I investigated how the two-way feedback between agricultural adaptation decisions of Kenyan farmers and the agro-hydrological system can be explicitly incorporated into a dynamic drought disaster risk model. Guided by four research questions, I reviewed literature, developed a conceptual framework, performed multi-method empirical data collection and analysis, and developed socio-hydrological agent-based modelling techniques. The results of this research and the answers to the research questions are summarised.

### *Improving modelling approaches for dynamic drought disaster risk models*

To respond to research question A '*What modelling approaches are suitable for simulating individual adaptive behaviour in drought disaster risk management?*' (Table 6.1 row 1), I summarised recent studies related to drought, adaptation modelling, socio-hydrology, risk adaptation behaviour and agent-based modelling. Based on these summaries, I argued that the interdependence of different actors, exposed systems, and drought hazards makes traditional disaster risk models inadequate for addressing the dynamic nature of drought disaster risks. I demonstrate that an agent-based socio-hydrological modelling design is more suitable for dynamic drought disaster risk modelling.

In Chapter 2, an overview of the use of ABMs for explicitly modelling individual drought adaptation actions is provided. Such models are particularly well suited to simulate the influence of bounded rational decisions on adaptation under varying biophysical, hydrological, and socio-economic conditions. I noted that it is key to apply a suitable psychological or economic behavioural theory to avoid *ad-hoc* rules about the decision-making process of the agents in the ABM. Therefore, a brief overview of four relevant theories for simulating the adaptive behaviour of farmers under agricultural drought disaster risk was given. The strengths and weaknesses of each theory were highlighted, and the need for applying empirical methods to collect individual-level data for the parameterisation and calibration of the chosen theory was emphasised.

The presented conceptual framework extends traditional risk modelling with two-way feedback between heterogeneous individual adaptation decisions and drought exposure, vulnerability, and hazard. The framework guides modellers to create dynamic drought disaster risk models based on theory and empirical data, supported by socio-hydrologic and agent-based approaches. Further, the framework indicates how the interactions between government policies and individual adaptation strategies; upstream and downstream decisions; and the effect of short-term and long-term priorities can be assessed. Hence, the framework provides a testing ground for understanding adaptive behaviour and drought disaster risk dynamics in an increasingly drought-prone environment.

### ***Comparing theoretical and empirical factors influencing adaptive behaviour***

To answer research question B, '*Which socio-economic, cognitive and policy factors influence the decision making of smallholder farmers facing droughts?'* (Table 6.1 row 2), I collected, compared, and combined empirical data with existing behavioural theories (protection motivation theory (PMT), theory of planned behaviour (TPB), expected utility theory (EUT)) for the case of smallholder farmers' adaptive behaviour in Kitui, Kenya. Multi-method field surveys including key informant interviews, stakeholder discussions, fuzzy cognitive mapping exercises, semi-structured questionnaires, and discrete choice experiments were executed. With the information collected, I evaluated the past and future adaptive behaviour of smallholder farmers and the applicability of existing behavioural theories to the case of Kitui.

In Chapter 3, the statistical and econometric analysis of the responses of the household survey is elaborated. This analysis firstly demonstrated that both adaptation costs and adaptation efficacy are of the highest importance to the adaptive behaviour of smallholder farmers. These factors are linked to field size (odds ratio of 1.05), performance of a cost-benefit analysis (odds ratio of 1.41), and perceived efficiency of the measure (odds ratio of 1.77), among other factors. Secondly, the analysis proved the significance of household knowledge on drought and adaptation as a driver for adaptation through the analysis of the proxy variable 'attended extension services' (odds ratio of 2.97). Thirdly, social networks (i.e., farm groups; odds ratio of 1.38) significantly influenced adaptation decisions. Fourthly, risk perception (fear from droughts; odds ratio of 1.23; trust in forecast; odds ratio of 0.84) and self-efficacy (perceived vulnerability; odds ratio of 0.83; faith in god as saviour; odds ratio of 0.42) play a role in explaining past adaptive behaviour. These results confirm the importance of risk appraisal, social norm, self-efficacy, and response cost and efficacy on adaptive behaviour under drought. These factors are components of existing theories of bounded rationality, but none of the evaluated theories could fully explain the observed behaviour.

I further demonstrated that tailored extension services (on average 1.51 times more likely to adapt), improved early warning systems (on average 1.54 times more likely to adapt), *ex-ante* cash aid (on average 1.11 times more likely to adapt) and low-interest credit schemes (on average 1.07 times more likely to adapt per % decreased interest rate) do increase the intention to adapt. While an aversion to the current situation of no new policy actions (on average 0.01 times 'more' likely to adapt under no additional governmental actions) was evident, there was significant heterogeneity in the preferences for these new policies.

### ***Testing assumptions on adaptive behaviour in drought disaster risk models***

To investigate research question C, '*How do different assumptions about the adaptive behaviour of smallholder farmers influence agricultural drought disaster risk estimations?*' (Table 6.1 row 3), I created a dynamic drought disaster risk model, ADOPT, which simulates the drought adaptation decisions of smallholder farmers over time. ADOPT combines the FAO crop model AquacropOS with an ABM capable of simulating different adaptive behavioural theories. ADOPT contains four bottom-up, on-farm adaptation measures: (1) applying mulch, (2) terracing farm field using the Fanya Juu technique, (3) creating additional shallow wells, and (4) applying drip irrigation and evaluates fluctuations in household food insecurity, poverty, and emergency aid needs due to drought disasters.

In Chapter 4, I used two behavioural theories (economic rationality under expected utility theory (EUT) and bounded rationality under protection motivation theory (PMT)) and one business-as-usual scenario to create decision rules for ADOPT. Under these three scenarios, I simulated the intention to adopt and the resulting adoption rate of adaptation measures over time. The results indicate that a combination of all four measures is the most effective way to reduce the negative impacts of droughts on crop yield, while a combination of a well and irrigation system has the highest initial costs but is also the most cost-efficient.

The results show that farmers under the economic rational scenario implement affordable adaptation measures at a fast rate (adoption rates at the end of the 30-year model run of 81%, 85%, 44%, 43% for mulch, Fanya Juu, wells, and drip irrigation, respectively), thereby increasing their maize yield. The adoption of drought adaptation measures occurs more gradually under the bounded rational scenario (simulated adoption rates of on average 34%, 43%, 10%, 5%, respectively), better matching the observed adoption rates from the surveys (12%, 45%, 16%, 6%, respectively). Furthermore, the bounded rational scenario exhibited variability in food security and poverty levels closest to the observed levels. This finding highlighted that the inclusion of PMT behaviour is better able to capture some of the variability in adoption decisions than the inclusion of EUT.

Moreover, the model runs indicated that the estimation of drought disaster risk and the need for emergency food aid can be improved using an agent-based approach. Ignoring individual household characteristics leads to an underestimation of food-aid needs: when the total harvest in the study area was assumed to be equally distributed among all households and all households could meet their food needs (mimicking modelling approaches which do not consider a heterogeneous set of actors), the estimated annual average aid needs were 48%-53% lower than under the scenario where access to food is heterogeneous, a more factual representation of reality. While these results should be interpreted with care given the assumptions and simplifications made, they highlight that current estimations of drought disaster risk and the need for emergency food aid can benefit from the household scale used in agent-based approaches.

### *Evaluating drought disaster risk dynamics under policy and climate change*

To explore research question D, '*Which external policy actions targeting smallholder farmers effectively reduce agricultural drought disaster risk under climate change?*" (Table 6.1 row 4), I applied ADOPT to investigate four top-down drought disaster risk reduction policies (tailored extension services, improved early warning systems, *ex-ante* cash transfers, and lower credit schemes) that can be implemented by governments or NGOs. In addition, I created six different climate change scenarios—wetter, hotter, wetter+hotter, drier, drier+hotter, and no change—to evaluate the effect of different drought frequencies (likelihood of occurrence of, respectively, 15%, 65%, 41%, 55%, 78%, and 24%) on maize yields. The AquacropOS results revealed a positive maize yield trend under wetter future climate conditions, under all types of adaptation measures. Hotter climate conditions reduce yields slightly (on average -13%), but paired with drier conditions, this results in 28% lower yields on average compared to the no climate change scenario over all management scenarios.

In Chapter 5, I demonstrate that all investigated top-down interventions have a positive effect on the uptake of adaptation measures. However, the positive effect on household resilience varies under different climate change scenarios and for different household types (wealthy, educated, large farm). As compared to reactive intervention, the proactive government scenario, 'preparing for drought disasters', increased

- the adoption of mulch (on average +90% under all climate scenarios)
- the adoption of Fanya Juu terraces (on average +33% under all climate scenarios)
- the adoption of shallow wells (on average +33% under all climate scenarios)
- the adoption of drip irrigation (on average +66% under all climate scenarios)

This proactive government scenario is estimated to lessen poverty and food security under most climate change scenarios. For example, under no climate change, a 10% decrease poverty compared to a 5% decrease under no intervention is estimated. This effect translates into reducing aid needs under most climate change scenarios. For example, under wet hot conditions, a 48% drop in aid needs compared to a 29% drop under no intervention is estimated. However, under dry or dry-hot conditions, a 25% increase in household food shortage is estimated, which is lower than under no intervention (+35%) but still an increase over time. This effect then leads to an increase in aid needs of 73% (compared to 117% under no intervention).

Compared to reactive intervention, the prospective government scenario 'mitigating drought disasters' alleviates multiple barriers to adoption at once and creates a significant increase in

- the adoption of mulch (on average +100% under all climate scenarios)
- the adoption of Fanya Juu terraces (on average +33% under all climate scenarios)
- the adoption of shallow wells (on average +800% under all climate scenarios)
- the adoption of drip irrigation (on average +2000% under all climate scenarios)

This prospective government scenario displays nonlinear positive synergies and results in reduced food insecurity, decreased poverty levels, and a drastically lower need for emergency aid. Even under hotter and drier climate conditions, over all climate scenarios an average reduction of 76% in aid needs is estimated. On the contrary, no intervention would lead to an average increase of +35% of emergency aid needs. However, it should be noted that it takes one to two decades to make a significant difference between the reactive stance and proactive or prospective top-down actions due to the delayed effect of the return-on-investment: significant gains for the first adaptation measure support further adoption of adaptation measures.

*Table 6.1: Overview of research questions, key highlights of the applied methods to answer them, and resulting answers.*

| Question | Method | Answer |
|---|---|---|
| What modelling approaches can account for adaptive behavior in drought disaster risk models? (Chapter 2) | • Review of existing research on drought disaster risk, human adaptation, and agent-based modelling.<br>• Development of conceptual framework that extends the traditional approach to risk modelling to include the two-way feedback between temporal adaptation decisions and drought exposure, vulnerability, and hazard.<br>• Discussion and comparison of (subjective) expected utility theory, prospect theory, planned behaviour theory, protection motivation theory.<br>• Establishment of guidelines for the integration of behavioural theories in agent-based models. | • A socio-hydrological, agent-based modelling approach focussing on individual and collective actions can best simulate the adaptive behaviour of different stakeholders.<br>• Such an approach could be a testing ground for understanding adaptive behaviour in a climate increasingly prone to drought.<br>• There is no single perfect-fitting behavioural theory.<br>• Empirical data at the individual level is needed for parameterisation and calibration of theories.<br>• The choice of processes and effects of drought disaster risk and the type of agents to be included should influence the choice of theory. |
| Which factors influence the decision-making process of farmers in the face of droughts (in Kenya)? (Chapter 4) | • Conducting of interviews with key informants and design of an extensive survey and experiment among local smallholder farmers in Kitui, the semi-arid eastern region of Kenya.<br>• Comparison and combination of this empirical data with factors from existing behavioural theories. | • Distrust of predictions and a strong belief in God are barriers to adaptation.<br>• Farmer groups and previous adaptation decisions stimulate the intention to take new measures.<br>• There is a clear heterogeneity in decision behaviour.<br>• Different components (risk perception, self-efficacy, social norms, response cost-benefits) of existing bounded rational theories significantly influence adaptation decisions. |
| Do different assumptions about adaptive behaviour influence agricultural drought disaster risk estimations? (Chapter 5) | • Development of a dynamic drought disaster risk adjustment model, ADOPT, which simulates water management decisions by smallholder farmers and evaluates food insecurity, poverty, and household emergency needs due to droughts.<br>• Comparison of risk outcomes under ADOPT assumptions based on conservation motivation theory, which describes bounded rationality, with business-as-usual and economic rational behaviour. | • Estimates of drought disaster risk and food aid need can be improved using an agent-based approach.<br>• Ignoring individual household characteristics leads to an underestimation of food aid need.<br>• The bounded rational scenario better reflects historical food security, poverty levels, and crop yields compared to the economic rational scenario. |
| How do external policy incentives influence agricultural drought disaster risk under climate change? (Chapter 6) | • Application of ADOPT<br>• Examination of the impact of four top-down drought disaster risk reduction policies that can be implemented by governments or NGOs (policies all included in current policy documents).<br>• Creation of climate change scenarios to assess the impact of changing drought conditions on agricultural risks for smallholder farmers.<br>• Evaluation of the robustness of the four policies under different potential future climates. | • Extension services promote the adoption of low-cost, new drought adaptation measures; credit schemes are useful for cost-effective but expensive measures; ex-ante cash transfers allow the least wealthy households to adopt low-cost known measures. Early warning systems prove more effective in reducing risk under wetter climate conditions.<br>• The combination of these four interventions shows mutually reinforcing effects, with a strong increase in uptake of measures resulting in dramatically lower emergency needs, even under hotter and drier climate conditions. |

## 2. The innovation of the ADOPT model

### *Agent-based agricultural drought disaster risk adaptation model*

This thesis innovates the use of ABM for dynamic drought disaster risk assessments in the context of policy and climate change. This thesis presents a dynamic agent-based drought disaster risk model, ADOPT, developed for a case study in Kenya as a proof-of-concept. The model simulates the effect of policies on smallholder farmers' drought resilience and evaluates the robustness of these policies under climate change. It focuses on smallholders, which in itself is not unusual. Indeed, the use of ABM in *ex-post* and *ex-ante* evaluations of agricultural policies and agricultural climate mitigation has been progressively increasing (Huber et al., 2018; Kremmydas et al., 2018). Examples of agricultural ABM can be found in the work of Berger and Troost (2011), Mehryar et al. (2019), Van Oel and Van Der Veen (2011), and Zagaria et al. (2021).

However, while ABMs have the potential to represent full 'closed-loop' couplings of environmental and social subsystems, this is not yet standard practice (Filatova et al., 2013). Further, the integration of ABMs with other hydrological or agricultural models to evaluate disaster risk is still in its infancy. Multiple ABMs currently evaluate the effects of individual water use decisions, for example on the propagation of droughts, or conversely evaluate the effect of agricultural droughts on farm income and food security (Schulze et al., 2017b). The ADOPT model, in contrast, does fully couple a biophysical model—AquacropOS—and a social model—simulating adaptation decisions using behavioural theories—through both impact and adaptation interactions. This advanced setup allows for simulating closed-loop feedback processes: the agro-hydrological conditions influence smallholders' adaptation decisions (through financial capacity, risk perception, adaptation benefits), which in turn influence the agro-hydrological system (affecting the vulnerability of crop production to droughts).

### *Complex, heterogeneous behaviour and theory*

In socio-environmental systems modelling, representing the human dimension—and the heterogeneity within agent groups—is seen as a grand challenge (Elsawah et al., 2020). Few studies have implemented empirically supported and complex behavioural theories in ABMs (Schrieks et al. 2021; Jager, 2021). The assumption of individual, heterogeneous, bounded rational behaviour by smallholders at risk is relatively new in drought disaster risk science (An, 2012; Kennedy, 2012; Taberna et al., 2020; Waldman et al., 2020). In ADOPT, farm households have the ability to learn, adapt, and recover from a drought shock, as the model considers both individual and community risk perceptions as well as changing adaptation knowledge, which can be communicated through a farmers' network. One of the few preceding studies including such complex adaptive behaviour of farmers is the research by van Duinen et al. (2015, 2016).

In addition to risk information, adaptation information is circulated in the modelled farmers' network in ADOPT, granting the social network a central role while accounting for biased (imperfect) knowledge related to adaptation benefits (see also Jager & Janssen, 2012). This inclusion of imperfect information ensures that the effect of maladaptation can be simulated.

Moreover, accounting for the effects of knowledge limitations, communication patterns, risk considerations, and self-efficacy that guide farmers' actual adaptation decisions allows for better representing barriers to adaptation in drought disaster risk adaptation models.

In the ADOPT model, the complex behaviour of smallholder farmers is based on established behavioural theories and is calibrated with empirical data collected through both qualitative and quantitative methods (Elsawah et al., 2020; Filatova et al., 2013a; Groeneveld et al., 2017a; O'Sullivan et al., 2016; Schlüter, Baeza, Dressler, Frank, Groeneveld, Jager, Janssen, McAllister, et al., 2017; Schrieks et al., 2021). This theory-driven and empirically supported setup is already present in some form in the work of Hailegiorgis et al. (2018), Keshavarz and Karami (2016), and Pouladi et al. (2019). The theories used in this thesis were selected at an early stage of model development to ensure that all elements of the theory were accounted for. Indeed, rigorous empirical methods (as suggested by Smajgl et al., 2011)—such as fuzzy cognitive mapping with stakeholders, individual household surveys, and economic experiments—were developed to obtain data on individual behaviour. Thus, the decision module of ADOPT relies on individual household data that allows for parameterising and calibrating the behavioural theories underlying the model.

### ***Drought disaster risk and risk reduction estimations***

A further novel feature is that ADOPT produces drought disaster risk proxies (i.e., drought impacts measured using socio-economic metrics) beyond the number of measures adopted, crop yield, and water use budgets, which have been used in multiple ABM studies. Dobbie et al. (2018) and Acosta-Michlik and Espaldon (2008) also tracked socio-economic metrics—food security and vulnerability to global change; however, they did not link these metrics directly to disaster risk or disaster risk reduction. Through the disaster risk setup, ADOPT is able to demonstrate the effect of adaptation actions on food security, poverty, and aid needs. It therefore is able to simulate the emergence of a disaster-induced poverty trap. Moreover, the micro scale of ADOPT allows for differentiating risk estimates for different types of smallholder farm households.

ADOPT has been used to estimate the impact of governmental and non-governmental policies on the reduction of drought disaster risk at the household level, which to my knowledge has not been done before. By simulating the decision process of farmers concerning the adoption of adaptation measures in a bottom-up manner, it is possible to calculate the effect of potential future policy actions on the individual factors that are part of this decision process. Instead of applying a statistical relationship between a policy and the adoption rate of adaptation measures, ADOPT simulates how those policies interact with the individual barriers to adaptation in a process-based way. ADOPT thus explicitly considers the heterogeneous effect of policies on smallholder farmers and can therefore be used to evaluate the effect of policies targeting specific groups.

## 3. Remaining challenges and scientific advances

This thesis presents a proof-of-concept for the use of agent-based dynamic drought disaster risk models as decision support tools for forward-looking policy assessment. As with any ABM that simulates human behaviour, the results are subject to considerable uncertainties given that the model is based on several assumptions. In ADOPT, the crop-water production and decision-making modules have been parameterised and partially calibrated based on existing theories and empirical data. Stakeholders have been directly involved in the definition and design of the model. Furthermore, a sensitivity analysis has been performed to evaluate the epistemic and aleatoric uncertainty and the effect of initialisation (as suggested by Muelder & Filatova, 2018). The brief sensitivity analysis of ADOPT confirmed that the uncertainty created by the model's implementation of behavioural theory does not critically influence the model results. However, the current model requires a few additional steps before it can be considered a prototype usable for prediction.

### *Stakeholder involvement to co-validate model processes*

The primary challenges associated with ABM stem from difficulties in data availability (Blair & Buytaert, 2015b, 2016a) and model parameterisation and validation (Grimm et al., 2006; Smajgl & Barreteau, 2017 O'Sullivan et al., 2016; Polhill et al., 2016; Schrieks et al., 2021). Comparing model results with observed dynamics in adaptation could help confirm the reality of the modelled adaptive behaviour (Filatova et al., 2013b), but a time series of real-world household-scale data regarding drought perceptions, adaptation intentions, and adaptation decisions does not exist. However, to overcome this data availability challenge, a further step of model validation could include the participation of multiple stakeholders with different knowledge of the system (Barreteau et al., 2004; Etienne, 2014; Gober & Wheater, 2015).

Stakeholder (e.g., farming community, policy makers, local experts) cooperation in the validation of ADOPT could be facilitated through role-playing games or workshops that triangulate model results with experts (Klügl, 2009; Lamarque et al., 2013; Rangecroft et al., 2020; Savic et al., 2016). Other ways of engaging stakeholders, including creative practices such as storytelling (e.g., Van Loon et al., 2020), could enable the co-creation of scenarios to evaluate the model, making the model results more useful to potential end users (Basco-Carrera et al., 2017; Le Pira et al., 2017). Stakeholder validation exercises may reveal the need for model adjustments: One promising way to improve ADOPT is the inclusion of the cost of drought disaster risk reduction policies—an element that is crucial for the full evaluation of these policies. This factor could easily be incorporated through collaboration with stakeholders if the latter help identify the financial and implementation details of the policies.

### *Upscaling and transferability*

ADOPT is parameterised for the test case of smallholder farmers in semi-arid Kenya, which makes it difficult to generalise the results to other places or other systems that could equally benefit from a dynamic model of drought disaster risk. However, the model framework can easily be adapted and parameterised if sufficient input data from another region are available. While it is often seen as a challenge to develop transferable methods and strategies between regions (Mishra et al., 2015), ADOPT could be applied for the evaluation of policy measures to increase drought resilience anywhere, from small- to large-scale farming systems in developing and developed areas. This application would require local data on adaptation behaviour (drivers and barriers), as context- and culture-specific factors influence adaptive behaviour (Noll et al., 2020). Additionally, agricultural production characteristics are needed to tailor AquacropOS-OS to new contexts.

ADOPT only includes four on-farm measures that affect crop production. Additional or other context-specific adaptation measures—such as changing planting dates, using drought-resistant seeds, and the use of sand dams—could easily be integrated into ADOPT. Doing so would require information on the effect of these measures on crop yield and on the specific drivers for adaptation of these measures. However, decisions on some measures need to be made on different time scales or might introduce other types of interaction among the agents. In that case, an understanding of the influence of power dynamics and complementary decisions on people's adaptive behaviour is necessary.

Moreover, since many of the world's vulnerable semi-arid areas are inhabited by pastoralists and most of the world's drought exposure occurs in cities, it would also be relevant to include pastoral and urban systems in a dynamic drought disaster risk model. Although integrating these different types of actors is also possible through an ABM setup as described in the conceptual framework of this thesis, this integration would require adding new modules to ADOPT. As crop production is only part of these systems, the interaction between adaptation decisions and risks to soil and surface water must be expanded. Moreover, the inclusion of other types of water users requires an understanding of the hierarchy of water use and the power relations involved among water users (Etienne, 2014; Nespeca et al., 2020).

### *Drought propagation and multi-risk framing*

ADOPT is designed as a drought disaster risk model and considers the systemic risk caused by (consecutive) droughts. One important aspect that can be added to ADOPT is a link to a spatially explicit hydrological model that is capable of evaluating the impact of multiple individual adaptation measures on the distribution of water resources in the river basin. Modelling this distribution on a basin scale is of great importance for spatial planning (Van Oel et al., 2012). With a good understanding of local catchment characteristics, positive and negative effects, locally and downstream, caused by widespread adoption of the measures can be considered and the effect of this widespread adoption on propagation of drought through the hydrological cycle can be evaluated.

Moreover, although it does not explicitly address them, ADOPT does take different types of drought (both meteorological and soil moisture droughts) and heat waves into account, as both temperature and evaporation directly influence crop growth in AquacropOS. As silo thinking rather than multi-risk thinking in disaster risk management may lead to adverse effects of adaptation measures on overlooked risks, ADOPT could be improved by considering other hydro-meteorological hazards (de Ruiter, 2020; Ward et al., 2020). For example, the effect of hail/frost and flooding could be included by adding their respective damage curves. Although the effects of low temperatures and heavy rain days are simulated in the model, they are currently assumed to only influence crop yields through limiting crop growth, and no direct destructive impact is simulated.

Consecutive events such as drought-to-floods or compound events such as pests during droughts can exponentially increase the adverse impact on crop yields and worsen the livelihood situation of smallholder farmers. Such multi-hazards would therefore be an interesting addition to ADOPT. However, this inclusion would require a deeper understanding not only of compound extreme events and their impacts, but also of the influence of diverse risk perceptions—and of the effect of a variety of in(ter)dependent adaptation measures—on farmers' adaptive behaviour.

## 4. A dynamic drought disaster risk adaptation model

This thesis offers proof-of-concept for a dynamic drought disaster risk adaptation model. Through developing a model that includes smallholder adaptation dynamics, this thesis improved the understanding of current and future agricultural drought disaster risk under socio-economic, policy and climate trends. The contribution of this research can be summarised in two outcomes for science and society:

### *Capturing adaptation dynamics in the context of drought disaster risk*

The first outcome of this thesis is a better understanding of the decision-making process in agricultural water management in the context of drought. Studying the adoption of adaptation measures by smallholder farmers in semi-arid Kenya through multi-method data collection revealed the drivers and barriers for adaptation to drought. Additionally, the findings revealed the connection between these drivers and barriers and the factors explaining adaptive behaviour in existing behavioural theories. This relationship between behavioural theories and field data on the micro scale can be used to parameterise socio-hydrologic, agent-based dynamic drought disaster risk models.

Furthermore, the heterogeneity of individual drought adaptation decisions was explored through combining theories and empirical data. The results demonstrated farm households' diverse preferences for drought disaster risk reduction actions. This empirical information can be directly used to develop and refine drought disaster risk reduction strategies in the semi-arid region of Kenya. Local policy makers can use these results to focus policies on the relevant barriers experienced by smallholder farmers, and to tailor these policies to specific groups or types of smallholder farmers.

### *Dynamic drought disaster risk models as a decision support tool*

The second outcome of this thesis is the demonstrated potential of a dynamic drought disaster risk model as a decision support tool for policies related to climate change adaptation and drought disaster risk reduction. The conceptual modelling framework I developed is broad and relatively non-technical, discussed at a level suitable for researchers without a strong background in the various fields of drought disaster risk and behavioural theories. It provides a guide on which critical aspects to consider when building models, as well as a direction for the future development of drought disaster risk models in all forms. Furthermore, by developing ADOPT, I demonstrated that an ABM approach and the application of bounded rational adaptation theory are promising ways to improve drought disaster risk estimates. I evidenced that ignoring individual household characteristics and their heterogeneous behaviour leads to an underestimation of food aid needs.

Moreover, I demonstrated the value of ADOPT through estimating the effect of four different drought policies on changes in drought disaster risk under six different climate change scenarios. With the ability to simulate the effects of knowledge limitations, communication patterns, risk considerations, and other factors that guide actual adaptation decisions, policy makers can design and test policies targeting both entire communities or specific groups. For example, one can use ADOPT to explore the choice of households to receive *ex-ante* cash transfers or the choice of communities to provide extra extension services or improved early warning systems (Government of Kenya, 2014; WFP, 2019)(Government of Kenya, 2014; WFP, 2019)(Government of Kenya, 2014; WFP, 2019)(Government of Kenya, 2014; WFP, 2019). The evaluation of the robustness of the examined disaster risk reduction policies under climate change can directly inspire policy makers to take timely action in agricultural areas in semi-arid Kenya. Therefore, this thesis offers a timely and valuable contribution to the Kenya agenda 2030 and to achieving the SDGs, in particular 'clean water for all', 'reduced inequalities', 'no poverty', and 'zero hunger'.

# ODD+D description ADOPT

## I. Overview

### I.i Purpose

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

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

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

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

### I.ii Entities, state variables, and scales

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

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

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

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

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

*Figure S1. UML diagram*

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

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

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

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

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

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

## I.iii Process overview and scheduling

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

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

Once a year, the household head decides whether they want to adopt a new drought adaptation measure. They make this decision based on their memory of past drought impacts, their perception of the adaptation costs, the knowledge on adaptation measures through their networks and training, and their perception of their own capacity. The adoption of a new measure changes the farm management of those farmers, directly changes their wealth (implementation costs) and the farm expenses for the following years (maintenance costs), and influences crop yield and crop vulnerability to drought – thus potential farm income - during the following years.

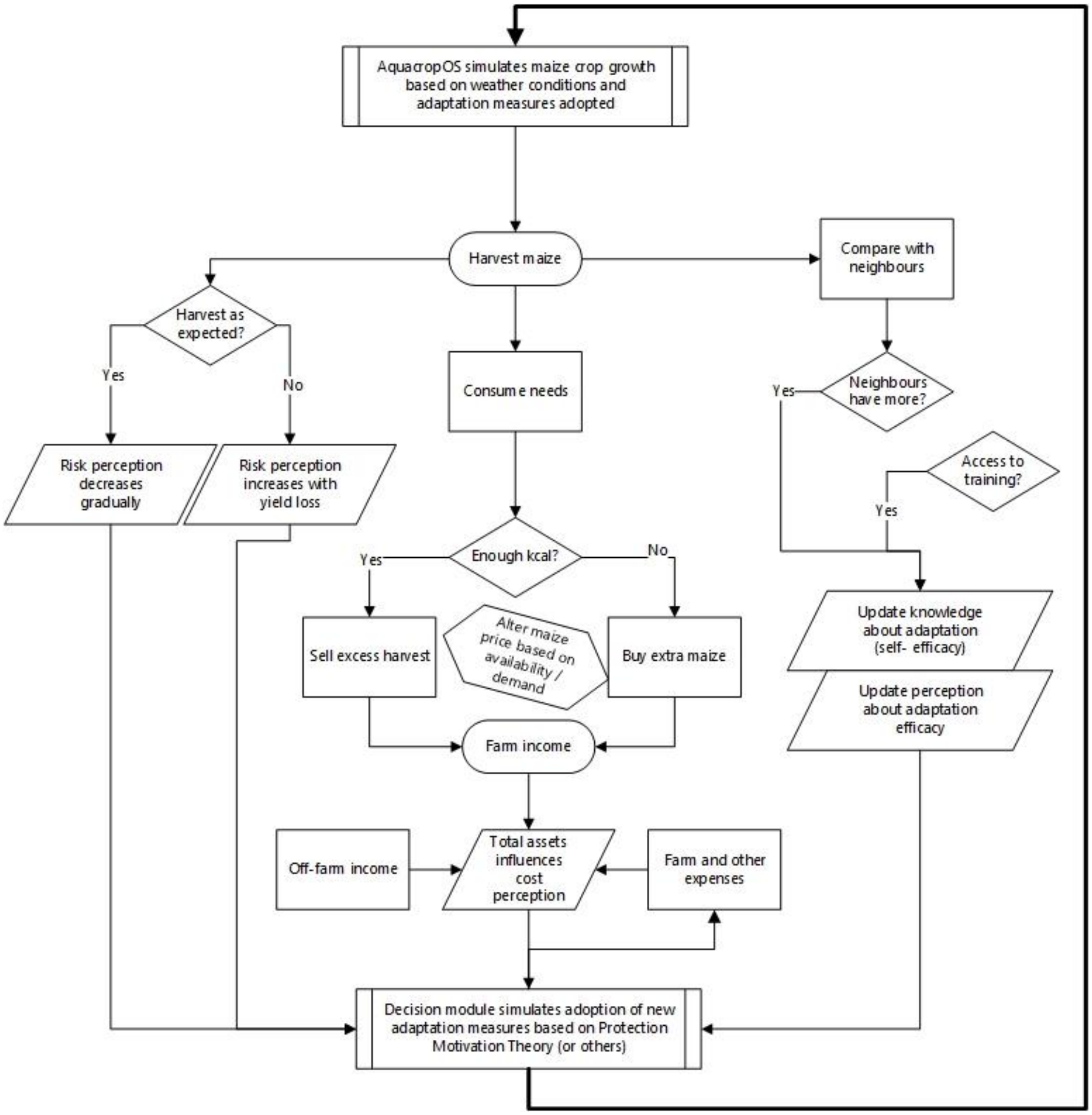


*Fig. Figure S2: Flowchart showing process overview*

## II. Design Concepts

### II.i Theoretical and Empirical Background

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

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

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

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

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

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

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

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

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

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

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

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

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

Data from the surveys are available on individual household level.

### II.ii Individual Decision Making

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

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

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

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

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

The Protection Motivation Theory (Maddux & Rogers, 1983) (see II.i) is used to explain the decision making process of the households. PMT consists of two underlying cognitive mediating processes that cause individuals to adopt protective behaviours when faced with a hazard (Floyd et al., 2000): It suggests that the intention to protect (in this study, the farmers' intention to adopt a new adaptation measure) is motivated by a persons' risk appraisal and the perceived options to cope with risks. The former depends on, for example, farmers' risk perception, on their own experiences with drought disasters and memory thereof, and on experiences of risk events in their social networks. The latter is related to different factors such as perceived self-efficacy (i.e., assets and sources of income, education level, and family size), adaptation efficacy (land size, adaptation measure characteristics) and adaptation costs (expenses in relation to their income) (Gebrehiwot & van der Veen, 2015; Keshavarz & Karami, 2016; van Duinen et al., 2015, 2016a). Households do not have any other objective or success criteria. A detailed description of how PMT is modelled – including the sensitivity analysis regarding the relative weights of the PMT factors - can be found in Wens et al. (2019): In ADOPT, farm households develop an intention to adapt (protect) for each potential adaptation measure (m) which changes every year (t). If a household has the financial capacity to pay for a considered measure (Stefanovi, 2015), the intention to adapt is translated into the likelihood the household will adopt this measure in the following years. (This can be influenced by having access to credit.) The actual adoption is stochastically derived from this likelihood to adopt a measure.

$$IntentionToAdapt_{t,m} = \alpha * RiskAppraisal_t + \beta * CopingAppraisal_{t,m}$$

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

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

$$RiskAppraisal_t = RiskAppraisal_{t-1} + (Drought_t * Damage_t) - 0.125 * RiskAppraisal_{t-1}$$

With $Damage_t = 1 - e^{-harvestloss_t}$

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 damage of a household is related to their harvest loss during the drought year, which is defined as the difference between their current and average harvest over the last 10 years.

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

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

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

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

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

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

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

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

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

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

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

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

No (only implicitly included, see II.ix)

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

No

## II.iii Learning

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

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

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

No

### II.iv Individual Sensing

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

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

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

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

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

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

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

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

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

No

### II.v Individual Prediction

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

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

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

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

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

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

### II.vi Interaction

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

In ADOPT, households interact with their neighbours, shaping risk awareness and response attitude (Nkatha, 2017; Okumu, 2013; van Duinen et al., 2016b). Such networks can enhance social learning and knowledge spill over, which influences people's adaptation intention and choice of specific measures (T. Below et al., 2010; Tongruksawattana, 2014). Smallholder households learn from the other households in their social network about the implementation and benefits of drought adaptation measure through neighbouring households' (Below et al 2010; Shikuku 2017). In ADOPT, exchanges with neighbours shape risk perception – the individual perception moves in the direction of the social network average – and also shape perceived adaptation effectivity. Moreover, households with no access to extension can only adopt measures already implemented by neighbours.

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

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

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

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

Communication is not explicitly modelled.

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

No coordination network exists.

### II.vii Collectives

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

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

### II.viii Heterogeneity

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

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

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

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

### II.ix Stochasticity

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

The likelihood to adopt a measure of a household is directly derived from the intention to adapt of the measure with the highest intention for that household. This is stochastically transferred into an actual decision whether or not to adopt the measure. For every time step of the simulation, a random number between 0-1 is drawn for each household; if this is lower than their adaptation intention (also between 0-1) and the household is able to pay for the measure, then the household adopts it. This probabilistic way of looking at adaptation intention and the stochastic step to derive the actual decisions allow to account for non-included factors introducing uncertainty in adaptive behaviour such as conservatism, social / cultural norms, physical health, ambitiousness etc. of the households. Moreover, also a stochastic perturbation (multiplied with a random number with average 1 and SD 0.1) is added to the maize yield per farm as calculated through AquacropOS. This additional heterogeneity-inducing step is done to include effects of pests and diseases on the income and food security of farming households.

### II.x Observation

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

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

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

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

# III. Details

## II.i Implementation

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

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

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

No(t) yet

## III.ii Initialization

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

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

*Table S1: 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 |

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

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

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

The initialisation values are based on observed household data. Survey data includes a short questionnaire among employees of the Kenyan national disaster coordination units (n=10), semi-structured expert interviews (n=8) with NGOs, governmental water authorities and pioneer farmers in the Kitui district in Kenya, and an in-depth questionnaire among 250 smallholder farmers in the central Kitui. Extra information is derived from household surveys of 2000, 2004, 2007 and 2010, conducted by the Tegemeo Agricultural Policy Research Analysis (TARAA) Project of the Tegemeo Institute. Besides, the model initialization draws heavily from reports of CIAT (CIAT & World Bank, 2015), FAO (Ansah et al., 2014), IFPRI (Erenstein et al., 2011) and the government of Kenya (Kitui County Integrated report 2013-2017, 2017), CCAFS (CCAFS, 2015), and from research (e.g., Muhammad et al., 2010).

### III.iii Input Data

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

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

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

- Wens, M. (2019). Survey report Kitui, Kenya: Results of a questionnaire regarding subsistence farmers' drought risk and adaptation behaviour. https://research.vu.nl/ws/portalfiles/portal/98864069/MissionRapport.pdf
- Wens, M (2018) Survey report Kitui, Kenya: Expert evaluation of model setup and preparations of future fieldwork https://research.vu.nl/ws/portalfiles/portal/98863978/MissionRapport2018.pdf

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

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

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

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

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

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

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

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

## III.iv Sub-models

### *What, in detail, are the sub-models that represent the processes listed in 'Process overview and scheduling'?*

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

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

AquacropOS was applied parameterized and calibrated following Ngetich (2011) and Omoyo (2015), who both analysed and approved the functioning of this model to simulate maize yield under different climates in Kenya.

The decision sub-model is described above in the sections about decision-making and theoretical foundations (II.ii). A more detailed description can be found in Wens et al 2020.

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

For AquacropOS, Table S3 and S4 give an overview of the parameters that are used. For the decision-making module, Table S2 gives an overview of the factors used.

*Table S2: 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 |

*Table S3: 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 (%) |

*Table S4: Crop parameters for maize AQUACROPOS in ADOPT*

| Value | Crop parameters for AquacropOS |
|---|---|
| 3 | : Crop Type (1 = Leafy vegetable, 2 = Root/tuber, 3 = Fruit/grain) |
| 1 | : Planting method (0 = Transplanted, 1 = Sown) |
| 1 | : Calendar Type (1 = Calendar days, 2 = Growing degree days) |
| 0 | : Convert calendar to GDD mode if inputs are given in calendar days (0 = No; 1 = Yes) |
| 16/03 | : Planting Date (dd/mm) |
| 31/08 | : Latest Harvest Date (dd/mm) |
| 5 | : Growing degree/Calendar days from sowing to emergence/transplant recovery |
| 40 | : Growing degree/Calendar days from sowing to maximum rooting |
| 80 | : Growing degree/Calendar days from sowing to senescence |
| 90 | : Growing degree/Calendar days from sowing to maturity |
| 40 | : Growing degree/Calendar days from sowing to start of yield formation |
| 5 | : Duration of flowering in growing degree/calendar days (-999 for non-fruit/grain crops) |
| 65 | : Duration of yield formation in growing degree/calendar days |
| 3 | : Growing degree day calculation method |
| 8 | : Base temperature (degC) below which growth does not progress |
| 30 | : Upper temperature (degC) above which crop development no longer increases |
| 1 | : Pollination affected by heat stress (0 = No, 1 = Yes) |
| 35 | : Maximum air temperature (degC) above which pollination begins to fail |
| 40 | : Maximum air temperature (degC) at which pollination completely fails |
| 1 | : Pollination affected by cold stress (0 = No, 1 = Yes) |
| 10 | : Minimum air temperature (degC) below which pollination begins to fail |
| 5 | : Minimum air temperature (degC) at which pollination completely fails |
| 1 | : Transpiration affected by cold temperature stress (0 = No, 1 = Yes) |
| 12 | : Minimum growing degree days (degC/day) required for full crop transpiration potential |
| 0 | : Growing degree days (degC/day) at which no crop transpiration occurs |
| 0.3 | : Minimum effective rooting depth (m) |
| 0.8 | : Maximum rooting depth (m) |
| 1.3 | : Shape factor describing root expansion |
| 0.0105 | : Maximum root water extraction at top of the root zone (m3/m3/day) |
| 0.0026 | : Maximum root water extraction at the bottom of the root zone (m3/m3/day) |
| 6.5 | : Soil surface area (cm2) covered by an individual seedling at 90% emergence |
| 37000 | : Number of plants per hectare |
| 0.89 | : Maximum canopy cover (fraction of soil cover) |
| 0.1169 | : Canopy decline coefficient (fraction per GDD/calendar day) |
| 0.2213 | : Canopy growth coefficient (fraction per GDD) |
| 1.05 | : Crop coefficient when canopy growth is complete but prior to senescence |
| 0.3 | : Decline of crop coefficient due to ageing (%/day) |
| 33.7 | : Water productivity normalized for ET0 and C02 (g/m2) |
| 100 | : Adjustment of water productivity in yield formation stage (% of WP) |
| 50 | : Crop performance under elevated atmospheric CO2 concentration (%) |
| 0.48 | : Reference harvest index |
| 0 | : Possible increase of harvest index due to water stress before flowering (%) |
| 7 | : Coefficient describing positive impact on harvest index of restricted vegetative growth during yield formation |
| 3 | : Coefficient describing negative impact on harvest index of stomatal closure during yield formation |
| 15 | : Maximum allowable increase of harvest index above reference value |
| 1 | : Crop Determinacy (0 = Indeterminant, 1 = Determinant) |
| 50 | : Excess of potential fruits |
| 0.02 | : Upper soil water depletion threshold for water stress effects on affect canopy expansion |
| 0.20 | : Upper soil water depletion threshold for water stress effects on canopy stomatal control |
| 0.69 | : Upper soil water depletion threshold for water stress effects on canopy senescence |
| 0.80 | : Upper soil water depletion threshold for water stress effects on canopy pollination |
| 0.35 | : Lower soil water depletion threshold for water stress effects on canopy expansion |
| 1 | : Lower soil water depletion threshold for water stress effects on canopy stomatal control |
| 1 | : Lower soil water depletion threshold for water stress effects on canopy senescence |
| 1 | : Lower soil water depletion threshold for water stress effects on canopy pollination |
| 1 | : Shape factor describing water stress effects on canopy expansion |
| 2.9 | : Shape factor describing water stress effects on stomatal control |
| 6 | : Shape factor describing water stress effects on canopy senescence |
| 2.7 | : Shape factor describing water stress effects on pollination |

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# ABOUT THE AUTHOR

I, Marthe LK Wens, am a researcher at the Vrije Universiteit Amsterdam. I have a Master Degree in Geography (KU Leuven and VUB, 2016), and combine social, economic and physical sciences in my research. Being part of the Water and Climate research group in the Institute for Environmental Studies at the VU Amsterdam, my recent research concerns the integration of adaptation behaviour in drought disaster risk and impact analysis. Focussing on Africa and Europe, I explore the use of machine learning and agent-based modelling tools to include local data and knowledge in risk assessments and turn these models into decision support tools for resilience building.

Over the course of my PhD, I collaborated closely with several institutes including the Geography group at the University of California, Santa Barbara, 510 of the Netherlands Red Cross, and CIMA research foundation. In the past 4 years, I (co-) authored 7 papers in international peer-reviewed journals and was contributing lead author to United Nations Office for Disaster Risk Reduction (2021) GAR Special Report on Drought 2021. I presented my work at several conferences such as EGU and AGU, and at institutes including Allianz and the Cardiff Water Research Institute. As part of my teaching responsibilities, I supervised BSc and MSc theses, and assisted as a lecturer in courses at AUC and at the VU. I also organised a summer school on modelling for water management in dry areas in Kenya as part of the VU capacity building project ASALI and organised a workshop series on water scarcity for the SENSE and AURORA networks.

Besides, I have been part of projects with the JRC, UNICEF, UNDRR, WMO, national RCS, and the World Bank. These projects related for example to co-creating drought disaster risk profiles for African nations (under the programme Building Disaster Resilience to Natural Hazards in Sub-Saharan African Regions, Countries and Communities), to assessing drought disaster risk on children (in the context of a collaboration between UNICEF, UNDP and UNWOMEN) and to forecast-based finance for food insecurity (GFDRR Challenge fund). During multiple of these projects, I facilitated capacity building events and dissemination workshops. I am member of the International Drought Management Programme, Panta Rhei research group Drought in the Anthropocene and the Dutch Drought Research network.

Currently, I am working as a postdoc researcher at the IVM contributing to the European Drought Observatory Risk Assessment by developing a pan-European sector-specific drought risk assessment methodology (https://edo.jrc.ec.europa.eu/edora/php/index.php?id=201). Moreover, I work on the co-creation of climate services through the inclusion of local knowledge and experiences in multiple living labs in Europe (https://icisk.eu/about-icisk/).

## LIST OF PUBLICATIONS


Teun Schrieks, Wouter Botzen, **Marthe Wens**, Toon Haer, Jeroen Aerts (2021) Integrating behavioural theories in agent-based models for agricultural drought disaster risk assessments. Frontiers in Water, 3, [686329]. https://doi.org/10.3389/frwa.2021.686329

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Sally Rangecroft, Melanie Rohse, Eddie W Banks, Rosie Day, Giuliano Di Baldassarre, Theresa Frommen, Yasunori Hayashi, Britta Höllermann, Karen Lebek, Elena Mondino, Maria Rusca, **Marthe Wens**, Anne F Van Loon (2021) Guiding principles for hydrologists conducting interdisciplinary research and fieldwork with participants. Hydrological Sciences Journal, volume 66 (2), 214-225, https://doi.org/10.1080/02626667.2020.1852241

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Philip J Ward, Marleen C de Ruiter, Johanna Mård, Kai Schröter, Anne Van Loon, Ted Veldkamp, Nina von Uexkull, Niko Wanders, Amir AghaKouchak, Karsten Arnbjerg-Nielsen, Lucinda Capewell, Maria Carmen Llasat, Rosie Day, Benjamin Dewals, Giuliano Di Baldassarre, Laurie S Huning, Heidi Kreibich, Maurizio Mazzoleni, Elisa Savelli, Claudia Teutschbein, Harmen van den Berg, Anne van der Heijden, Jelle MR Vincken, **Marthe Wens** (2020) The need to integrate flood and drought disaster risk reduction strategies. Water Security, volume 10, 100070, https://doi.org/10.1016/j.wasec.2020.100070

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**Netherlands Research School for the**
**Socio-Economic and Natural Sciences of the Environment**

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born on 12 February 1993 in Leuven, Belgium

has successfully fulfilled all requirements of the
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A K A D E M I E V A N W E T E N S C H A P P E N

The SENSE Research School declares that **Marthe L. K. Wens** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 46.3 EC, including the following activities:

**SENSE PhD Courses**

- Environmental research in context (2017)
- Research in context activity: 'Organising and moderating a Series of workshops with invited speakers related to Water scarcity' (2018)

**Selection of Other PhD and Advanced MSc Courses**

- Agent-based modelling for resilience, WASS graduate school (2017)
- HPC and Big Data Course UVA / SurfSara (2017)
- Collaborative Research Workshop - Drought in the Anthropocene, University of Freiburg (2017)
- Scientific writing in English, VU-Amsterdam (2018)
- Collaborative Research Workshop on modelling risk and resilience in human and natural systems, Universität Bern (2019)

**External training at a foreign research institute**

- Research stay at the Geography Department, UCSB, United States of America (2018)

**Selection of Management, societal impact and Didactic Skills Training**

- Supervising 6 MSc student and two BSc with thesis (2018-2021)
- Lectured during the BSc/MSc courses , at the AUC "Water management" course, the Hydrology "Water Risks" course and at ERM "Water and Climate Systems" course (2021)
- Teaching a summer school on Water Management in dry regions, VU CIS, South Eastern Kenya University (2019)
- Presenting research on integrating adaptive behaviour in drought risk assessment, World BankWashington DC (2018)
- Dissemination workshops / stakeholder facilitation, CIMA/UNDRR, SS Africa (2018-2019)

**Selection of Oral Presentations**

- *Simulating dynamic drought adaptation behaviour of agricultural stakeholders using agent-based models*. IEMSS, July 2018, Fort Collins, United States of America
- *Drought adaptation behaviour of agricultural stakeholders: an agent-based model.* AGU conference, December 2018, Washington DC, United States of America
- *Integrating human adaptive behaviour dynamics n agricultural drought risk assessment*. May 2021, Cardiff University Water Resource institute invited online talk
- *Education, financial aid and awareness to reduce smallholder farmers' vulnerability to drought under climate change*. EGU conference, April 2021, Vienna, Austria

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