Climate Risk Management 30 (2020) 100247

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Farmer forecasts: Impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa

Zack Guido [a,b,*], Andrew Zimmer [c], Sara Lopus [d], Corrie Hannah [c], Drew Gower [e], Kurt Waldman [f], Natasha Krell [g], Justin Sheffield [h], Kelly Caylor [g], Tom Evans [c]

[a] Arizona Institutes of Resilience, University of Arizona, 1064 E. Lowell Street, Tucson, AZ 85719, USA
[b] School of Natural Resources and Environment, University of Arizona, 1064 E. Lowell Street, Tucson, AZ 85719, USA
[c] School of Geography and Development, University of Arizona, 1064 E. Lowell Street, Tucson, AZ 85719, USA
[d] Department of Social Sciences, Building 47-19, California Polytechnic State University, San Luis Obispo, CA, USA
[e] Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, USA
[f] Department of Geography, Indiana University, 701 E Kirkwood Ave., Bloomington, IN 47405 USA
[g] Department of Geography, University of California, Santa Barbara, CA, USA
[h] School of Geography and Environmental Science, University of Southampton, Southampton, United Kingdom

ARTICLE INFO

Keywords:
Climate information services
Seasonal climate forecasts
Climate perceptions
Agricultural decision-making
Smallholder
Maize

ABSTRACT

Seasonal climate variability frequently undermines farm yields, reduces food availability, and lowers income. This is particularly evident among small-scale agricultural producers in both irrigated and non-irrigated agroecosystems in the Global South where maize cultivars constitute a critical component of food production. In these systems, farmers make climate-sensitive decisions that include the selection of late- and/or early-maturing seed varieties, the diversity of seed varieties sown, and when to plant. Farmers' expectations of future rainfall would therefore seem to be critical determinants of agricultural outcomes and foreshadow climate impacts. However, few studies have quantified the linkages between on-farm decisions and farmer seasonal predictions. We report on detailed household and phone surveys of 501 smallholder farmers in central Kenya based on the 2018 growing seasons and expectations for the 2019 March-April-May growing season. We show that farmers' expectations of the upcoming seasonal rainfall have important associations with selections of seed maturity varieties and the number of maturing varieties farmers expect to plant and less important associations with the seeds' planting dates. Furthermore, we show that 79% of the farmers form an expectation of the future seasonal climate and about two-thirds of them formed expectations based on a heuristic that connects the past climate to future seasonal conditions. More problematically, one-third of the farmers formed their rainfall expectation based on the prior season, and we show that no such correlation exists in observational data nor is correlation of seasonal rainfall supported by current understanding of climate variability. These results highlight the challenges farmers face in anticipating seasonal rainfall, which has implications for crop diversification and choices to adopt drought tolerant cultivars. The results suggest that farmers' expectations of upcoming seasonal climate are important measures of farm decision-making.

* Corresponding author at: Arizona Institutes of Resilience, University of Arizona, 1064 E. Lowell Street, Tucson, AZ 85719, USA.
E-mail address: zguido@email.arizona.edu (Z. Guido).

https://doi.org/10.1016/j.crm.2020.100247
Received 21 August 2019; Received in revised form 16 July 2020; Accepted 4 October 2020
Available online 9 October 2020
2212-0963/

1. Introduction

While climate change presents relatively new challenges to smallholder farming systems, seasonal climate variability has been a significant hazard for agriculture producers across the world for millennia. As a result, farmers have developed strategies to make crucial decisions about what, when, and where to plant. These strategies draw on unique mixes of individual resources, planning, experimentation, and improvisation, and they can combine situated knowledge and external expertise (Carr and Onzere, 2017; Crane et al., 2009; Orlove et al., 2010; Roudier et al., 2014). In so doing, farmers match their decisions to their expectations of future rainfall (Roncoli et al., 2002). Yet, despite their best efforts, erratic rainfall frequently has a direct negative effect on crop production (Ray et al., 2015), particularly in rain-fed systems, as well as an indirect effect via the influence of rainfall on pests and diseases (Avelino et al., 2015). Both pathways undermine farm yields, reduce food availability, and lower income.

The impact of climate variability is of particular importance for maize producers. Maize is one of the most widely cultivated and economically significant crops globally. It is grown on about 240 million hectares worldwide (FAOSTAT, 2019) and supplies at least 30% of the food calories to more than 4.5 billion people, many of whom live in developing economies (Shiferaw et al., 2013). By some estimates, climate changes will cause declines of global maize production by about 10% in coming decades, raising important development challenges in the sector. This is particularly true for Sub-Saharan Africa (SSA) where maize is the principal staple crop (Cairns et al., 2013), is largely grown on small-scale plots, and provides approximately 45% of the total food calories (Shiferaw et al., 2013). Despite the importance of maize in SSA, yields have stagnated since the 1990s and the region has the unfortunate distinction of producing the lowest yields in the world (Ray et al., 2012). Similar to other maize growing regions, multiple social and environmental stressors contribute to production challenges in SSA, including droughts, plant pests and diseases, low input availability and use, inappropriate seed germplasm, and difficulty obtaining better-performing seed varieties (Cairns et al., 2013; Fisher et al., 2015). For example, newly developed drought tolerant maize varieties out-perform commonly used varieties (Cairns et al., 2013; Fisher et al., 2015; Smale and Jayne, 2004), in some cases by as much as 137% (Fisher et al., 2015); however, adoption of these varieties in many regions remains low (Fisher et al., 2015). Moreover, the high reliance on rainfed agriculture in SSA further exacerbates maize sensitivity to weather and climate change.

Small-scale rural livelihood systems in SSA tend to be complex. Farmers produce multiple crops following complicated calendars, integrate livestock with farming, and engage in diversified on-farm and off-farm activities to which they allocated household resources. Nonetheless, the central importance of maize production in many parts of SSA and its vulnerability to weather and climate makes the potential benefit for weather and climate information as a risk management tool among the highest in the world (Cooper et al., 2008).

The selection of seed varieties and when to plant them are two of the more consequential decisions farmers make each crop season. Factors that influence these decisions at the farmer-level are varied and complex (Waldman et al., 2017; Ziervogel et al., 2005). Nonetheless, a close connection between farming outcomes and weather and climate suggests that expectations about near-term climate—formed from either a technical forecast or local knowledge—play a role for on-farm decisions. Despite this theoretical connection, however, quantitative empirical evidence that links expectations of the future seasonal climate with decisions is scarce in the developing world. In the large literature studying the use of technical seasonal climate forecasts (SCF), most studies either report very limited actual use or only evaluate their potential use (Dilling and Lemos, 2011). We are similarly unaware of any studies that quantitatively associate farmers' personal forecasts to their on-farm decisions in the literature focusing on local knowledge in climate risk management.

In this analysis, we investigate the proposition that farmers' expectations of season climate are associated with different planting decisions. While this proposition may appear self-evident, studies and programs that connect climate and weather information to farmers often assume that climate conditions are determinants for decisions. However, there are many systemic and idiosyncratic reasons this assumption may not hold. Among those are access to seeds and other productive assets (Eakin et al., 2014; Ingram et al., 2002; Waldman et al., 2017), knowledge (Meijer et al., 2015), risk perceptions and tolerance (Rockström et al., 2002; Slovic and Peters, 2006), and household dynamics (Carr and Owusu-Daaku, 2016). Moreover, exploring the links between climate expectations and decisions may reveal import biases that shape decisions (Kunreuther and Weber, 2014).

We draw on household data of 501 farmers collected during an in-person household survey in the summer of 2018 and, five months later, during phone surveys of the same farmers. This analysis makes three contributions. (1) We quantified the fraction of farmers who use weather and climate forecasts, either of personal or technical origin, for different agricultural decisions. (2) We identify statistically significant associations between farmers' expectations of future seasonal rainfall and their decisions about the maturity period of maize cultivars, the choice to plant multiple cultivars with differing maturation periods, and their sowing date. (3) We identify and discuss the reasons that underlie their expectations and whether farmers perceive changes in their ability to forecast the future. In addition, this study was motivated by the idea that making explicit ideas that shape decisions is a first step toward enabling communities, individuals, and support systems to manage better climate and weather variability (Adger et al., 2009). With this in mind, we conclude by discussing the implications of our results within the context of climate resilience-building activities.

2. Climate information use in agricultural risk management

The use of weather and climate information in agricultural decision-making has been largely explored in two main branches of research. One branch focuses on the role of local knowledge in farm management. The second focuses on the use of technical information in agricultural risk management, most often in the form of seasonal rainfall forecasts produced by national meteorological services and the World Meteorological Organization (WMO) regional climate centers. Both have rich histories of scholarship.

Studies on local knowledge have documented the various ways farmers' observations of the natural world shape beliefs about the future. Orlove et al. (2000) showed that Peruvian farmers adjusted the planting dates of potatoes based on the brightness of stars; their forecasts also had a basis in western theories of climate science because of the link between high-level clouds and ENSO, which is a major driver of climate variability in the region. Roncoli et al. (2002) found that farmers in Burkina Faso forecast the future based on crop yields from different tree species. In many other regions, local knowledge is an important social and cultural tool for understanding the future, with technical forecasts providing complementary information (Roncoli et al., 2002; UNESCO, 2019; World Bank, 2015). Farmers thus draw on personal experiences and the social circumstances in which they live to manage weather and climate uncertainty. Their strategies cut across a continuum, taking on forms such as income diversification, in-season adjustment to changing environmental conditions, and post-seasonal sale of assets (Cooper et al., 2008). Often, the strategies are "risk-spreading," and fail to take full advantage of favorable conditions (Cooper et al., 2008).

Weather and climate forecasts are considered tools to help manage risk and enable people to better adapt to environmental uncertainty (Smit and Wandel, 2006). Research on the use of technical seasonal forecasts (SCF) dates to Glantz (1977), who investigated the value of a fictional seasonal rainfall forecast in West Africa as well as the constraints on its use. Subsequently, advances in both climate science and prediction have enabled the production of seasonal rainfall forecasts, which have been incorporated into operational outlooks from regional climate centers and national meteorological departments in SSA (Ogallo et al., 2008; Sheffield et al., 2014). Research has documented the predictive skill of SCFs as a function of the region and lead time, and their potential value (Sheffield et al., 2014; Yuan et al., 2013). While many studies acknowledge a potential value in SCFs, a large body of research has documented barriers to their use. The barriers include limited human, social, and financial capital (Eakin et al., 2014; Glantz, 1977; Ingram et al., 2002; Tall et al., 2018). For example, Ingram et al. (2002) found that farmers in Burkina Faso would need to possess basic agricultural technologies like plows, new crop varieties, and fertilizers to fully benefit from precipitation forecasts. Likewise, Eakin et al. (2014) noted that while many climate adaptation efforts develop tools (such as SCF) to anticipate and respond to weather and climatic threats, the underlying poverty and political marginalization limit their effect on reducing vulnerability.

Beyond deep structural barriers exist other challenges. In a recent review on the use of weather and climate information in SSA, Nkiaka et al. (2019) identified capacity building among national meteorological departments and sustained interactions between diverse stakeholders, including meteorologists, extension agents, and farmers as ways to increase use. A lack of knowledge about available products and how to interpret them are partial explanations for the low usage rates in many countries (Tschakert et al., 2010). The use of information is thus a complex process influenced by both extrinsic and intrinsic conditions that need to be taken into account (Meijer et al., 2015).

3. Farming context in central Kenya

Our study site is located in central Kenya on the northwest side of Mount Kenya (Fig. 1). Since Kenya's independence in 1963, the

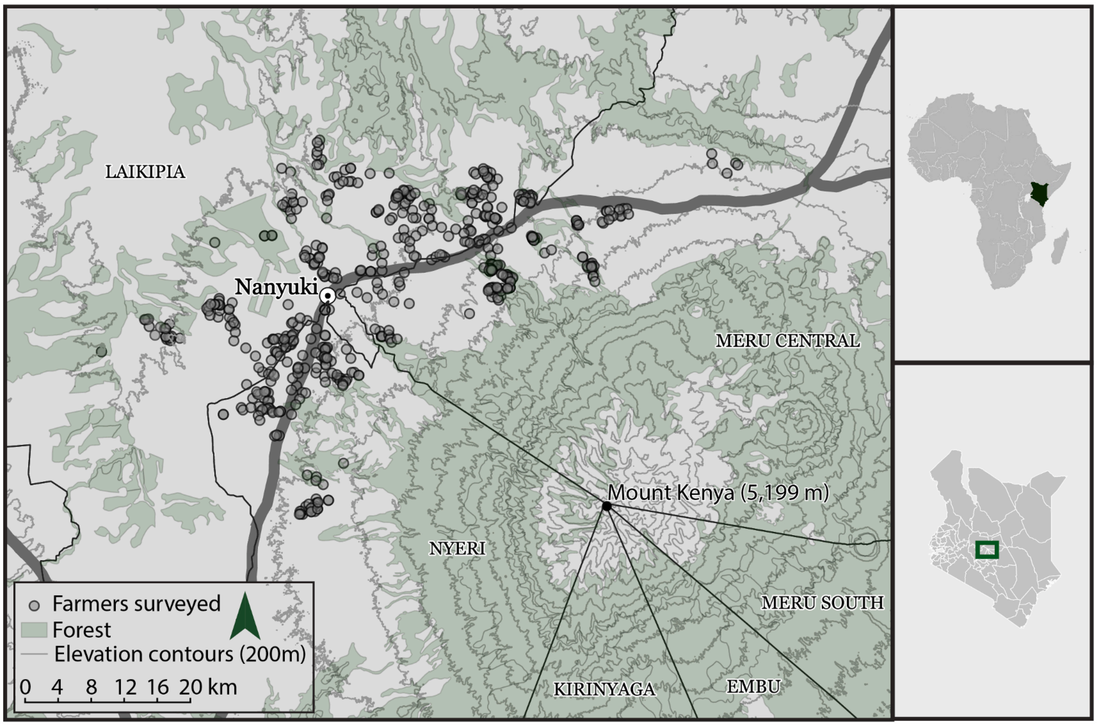

Fig. 1. Study location and surveyed households.

area has experienced rapid social and agricultural change. Independence brought land distribution programs that led to internal migration to the region (Ulrich et al., 2012). The population of the surrounding Laikipia County increased from 60,000 in 1960 to more than 400,000 residents in 2009, and land use changed from predominantly ranching to small-scale mixed cropping systems (Ulrich et al., 2012). Maize cultivation has since played an important role both economically and culturally.

Although agriculture is primarily a household activity, groups of farmers often form associations in order to improve their access to credit, water management, and other productive resources (Lopus et al., 2017; Ulrich et al., 2012). Household agricultural decision-making is primarily dictated by the patriarch, but there are important nuances. Krell et al. (2020) stated that in male-headed households, gender roles in farming are both different in type and in decision-making authority. The authors cited an example of female Kenyan dairy farmers having less control over household choices. However, in cases where the patriarch works off-farm, women make more of the agricultural decisions. As circumstances dictate, both male and female household members seek off-farm income (Ulrich et al., 2012). Thus, there can be substantial diversity in decision-making at the individual household level.

The maize yields of many smallholder farmers in Central Kenya are affected by conditions related to access to land, labor, markets, as well as environmental disturbances like pests and drought. Further constraining yields is uneven access to agro-chemicals and certified seeds (Bryan et al., 2013). Season to season variability in production conditions have compelled farmers to diversify their crops and income sources as a risk reducing strategy (Ogalleh et al., 2012). These characteristics are common to farming across Kenya and, to a large extent, Sub-Saharan Africa (Hassan and Nhemachena, 2008; Jayne et al., 2010; Mumo et al., 2018).

The farmers in our sample exemplify the aforementioned characteristics in many ways (Table 1). Among this group, a typical household consists of about four members, the average farm size is about 2.5 acres (~1 ha), and families allocate at least a portion of their farm to maize. In addition to maize, farmers cultivate on average six other crops, including beans, leafy greens, onions, and potatoes (Supplemental Fig. 1). About 81 percent of the families also own livestock. In the area, between 1997 and 2010, the lack of water was the largest constraint farming households faced in trying to improve their lives (Ulrich et al., 2012). Now, about 78% of the surveyed farmers belong to a Community Water Projects (CWP). A CWP supplies domestic and irrigation water to individual households from local streams via pipe networks (Lopus et al., 2017; McCord et al., 2017). When streamflow is sufficient, CWP membership can help farmers extend their growing season and mitigate the impact of dry spells or a false beginning of rains at the start of the growing season (Ericksen et al., 2011). However, water supply varies seasonally and annually and has been reduced in recent years as a result of increased regional demand.

Farmers we surveyed live at elevations between 1,350 m and 2,690 m, with higher areas receiving more rainfall. The area receives on average 700 mm of rain each year, with about 1,500 mm falling on the upper slopes of Mount Kenya and about 500 mm falling on the arid savannas at lower elevation to the north and west (Gichuki et al., 1998). A similar gradient occurs in the frequency of rainy days, while no such pattern exists for rainfall intensity (Camberlin et al., 2014).

Rainfall in the region occurs primarily within two seasons: the “long rains” lasting roughly from March to May (hereafter MAM rains) and the “short rains” lasting roughly from October to December (hereafter OND rains). Some areas west of the study site also experience a third wet season called the “continental rains” that occur between June and September (Gichuki et al., 1998). In general, the MAM rains provide the most seasonal rainfall but are also less spatially coherent (Mugo et al., 2016), while the OND rains exhibit more interannual variability (Hastenrath et al., 2011; Nicholson, 2017). The MAM rains have been historically the more important agricultural season. For example, all farmers planted during the 2018 MAM season, whereas only 252 of the 501 farmers (50%) planted in the 2018 OND season.

Seasonal rainfall variability has many influencing factors. While the northward and southward passage of the Intertropical Convergence Zone (ITCZ) over the equator is the primary mechanism for equatorial rainfall seasonality, both the MAM and OND rains are influenced by teleconnections with the Indian and Pacific Oceans (Nicholson, 2018). Studies have found that the interannual variability of OND rains correlates with the strength of zonal winds over the Indian Ocean (Hastenrath et al., 2011; Nicholson, 2015). Other studies have shown correlations between the magnitude of MAM rains and sea surface temperatures in the Indo-Pacific (Lyon and Dewitt, 2012; Williams and Funk, 2011), but such correlations tend to be weak (Liebmann et al., 2014). These teleconnections lead to low skill—a measure of the degree of agreement between the forecast and observations—for seasonal MAM rainfall predictions; the skill of OND rainfall forecasts are higher (Nicholson, 2014a; Shongwe et al., 2011).

Table 1
Descriptive statistics of farmers in our sample; SD is standard deviation. Asterix denotes variables we used as control variables in the regressions. [1]Education ranges from 0 (no formal schooling) to 8 (completed post-secondary schooling).

Variables	Mean	SD	Range	N
Household size	3.87	1.21	2–11	499
Gender of of interviewed farmers (1 = male)*	0.45	0.50	0–1	485
Age of interviewed farmers*	50.5	11.9	21–80	497
Education of interviewed farmers*,[1]	4.37	1.92	1–8	495
Farm elevation (m)*	2,029	227	625–3,676	500
Total land size (acres)*	2.50	2.29	0.13–17.0	499
Contact with extension (1 = yes)*	0.51	0.50	0–1	498
Community water project (CWP) membership (1 = yes)*	0.78	0.42	0–1	499
Lived in areas form more than 10 years (1 = yes)	0.84	0.37	0–1	500
Number non-maize crops grown	5.94	3.10	0–15	501
Number of cattle owned	2.38	2.03	0–18	496

The Kenyan Meteorological Department (KMD) provides technical forecasts that include 1- to 5-day weather forecasts, 1-month climate forecast, and SCFs for the MAM and OND periods. The WMO regional climate center—IGAD Climate Prediction and Applications Centre (ICPAC)—based in Nairobi, Kenya also produces SCFs. The SCFs for precipitation are probabilistic forecasts for total accumulated rainfall over a 3-month period; they are usually presented as the likelihood that precipitation will be within one of three tercile categories commonly referred to as above-, near-, and below-normal. These forecasts are disseminated several weeks in advance of the forecast season via traditional media, social media platforms, and personal networks stewarded by KMD staff located in district offices.

4. Methods of data collection and analysis

We conducted a survey of 501 farming households in June and July 2018. In December 2018 and January 2019, we conducted a follow-up phone survey of the same households to match farmer's expectations for upcoming growing seasons to actions taken. Fig. 1 displays the spatial distribution of the surveyed households. The farmers we surveyed were selected in order to continue a longitudinal dataset that has investigated management of farms and CWPs (Gower et al., 2016; Krell et al., 2020; Lopus et al., 2017; McCord et al., 2015, 2017). The design of that initial survey effort was a spatially stratified random sample of 30–40 households in each of 25 CWPs. A team of eight Kenyan enumerators and research assistants conducted the household survey in person and in the preferred language of the farmer. The household interview was based in part on a sustainable livelihoods approach (Scoones, 1998) and recorded demographic information, agricultural farming practices, social interactions, and information about weather and climate information use, among other topics. For questions about information use, we defined "use" as a specific action motivated by access to the information. For example, for farmers who stated they used the weather forecast, we inquired how. Each household interview lasted 1–1.5 h. In the follow-up phone survey, we contacted farmers from the same households to gather information from the OND 2018 growing season and planned activities for the upcoming MAM 2019 growing season. Phone interviews lasted approximately 20 min. Two members of the enumerator team that conducted the household surveys conducted all phone interviews.

Our analysis focuses on expectations of future rainfall and farmer decisions. To gather expectations of future rainfall, we asked farmers, (1) What type of rainfall do you expect in the upcoming rainy season? And, (2) Why do you think the rain during the upcoming season will be this way? The former question was fixed-response, whereas the latter question was asked in open-ended form. We analyzed the responses of the open-ended question for key themes and coded them into a fixed-response question that we repeated in the subsequent phone survey.

In relation to a farmer's choices of seed varieties, we asked farmers to identify the seed's maturation period: early, intermediate, or late. Access to seeds can be a constraint on the seeds planted. In asking for the seed categories that farmers intend to plant, we assume the responses subsume issues of access. For example, a farmer would not expect to plant a late-maturing variety if they did not possess it and could not buy it. Although seed producing companies often publish ranges of maturity periods, our interest is in the seed maturity farmers think they are planting. With more than 30 different maize seed varieties available to farmers, there can be differences between farmers' perception of the maturity period and the maturity period stated by seed producing companies (Waldman et al., 2017). In seeking what farmers perceive as the seed maturity period, we used categories both farmers and seed companies use: (e.g. early, intermediate, and late). While different companies define these categories slightly differently, the maturity periods for each are roughly less than three months, three to five months, and greater than five months, respectively.

To estimate the expected planting dates, we first asked farmers the month in which they expected to plant, followed by a subsequent question that asked for the week in that month in which they expected to plant. We converted this month and week pair into a Julian day. For the week number stated, we assigned the highest value of that week—for example, the third week was assigned a value of 21. This creates an uncertainty of up to seven days in our planting day estimate.

We use a set of independent logistic models to estimate the associations between farmers' rainfall expectations and their choices of seed maturation periods: one for each of the three maturity categories and a fourth for farmers who intended to plant several maturity categories. The dependent variables are binary, indicating in each of the first three models whether a farmer intends to plant that particular seed maturity variety, and, in the fourth model, indicating whether a farmer intends to plant more than one seed maturity variety. To estimate the associations between farmers' rainfall expectations and choices of planting date we use a linear regression model.

We specify the models based on an informed view of the setting, controlling for household- and individual-level attributes that in theory exert an influence on the planting decisions (e.g. Gower et al., 2016; Lopus et al., 2017; McCord et al., 2015, 2017). For example, in a study of many of the same households, field size, interactions with agricultural extension officers, and suitability of environmental conditions related to crop patterns (McCord et al., 2015). The control variables are presented in Table 1. They help account for farmer heterogeneity and relate to measures of capital often used in livelihood and vulnerability studies (Guido et al., 2020; Scoones, 1998). For example, interactions with extension officers and interactions with community water groups are measures of social capital that can influence access to information (Nkiaka et al., 2019; Tongruksawattana, 2014) and trust in that information (Paul et al., 2016). Elevation influences rainfall, a form of natural capital. Farm size is associated with financial capital and affects decisions to adjust to climate changes (Tongruksawattana, 2014). Similarly, education is a form of human capital that relates to access to new ideas and risk tolerance (Knight et al., 2003; Rahm and Huffman, 1984).

To account for covariance among neighboring households, we cluster the standard errors at the community level. We do this because community-level similarities in rainfall and CWP water delivery, for example, may influence chosen maturation varieties and planting dates. Clustering the standard errors affects the standard error on all variables, adjusting the significance of each coefficient but not the value of the coefficients themselves.

The coefficients in the logistic regressions are interpreted as odds ratios and are compared to the baseline expectation that upcoming seasonal conditions will experience “the same amount of rain as a normal year.” Coefficient values less than one convey that the corresponding variable is associated with a lower-than-baseline expectation to plant a given maturation variety, whereas values greater than one represent a higher-than-baseline expectation to plant that variety.

5. Results

5.1. Farming activities informed by expectations of future rainfall

Technical forecasts provided by the KMD include 1- to 5-day weather forecasts, 3-month SCFs of precipitation prior to the OND and MAM seasons, and a 1-month rainfall forecast. Of the 501 farmers we surveyed, more than 87% were aware of the weather forecasts and 69% and 57% were aware of MAM and OND seasonal forecasts, respectively. While the 1-month forecast was least known, a relatively high percent of farmers, 40%, were still aware of it.

Awareness, however, may not lead to use. We therefore asked the farmers if each of the four information types were used in specific agricultural decisions. Fig. 2 displays the percentage of farmers whose decisions were, in some way, shaped by the different forecasts. It conveys three principal findings. First, weather and seasonal forecasts had high usage for choices related to planting dates, crop types, and crop varieties. Second, the MAM forecast was used more frequently than the OND forecast. And third, a large fraction of farmers did not use the forecasts.

The results in Fig. 2 also highlight the many types of on-farm decisions that tend to be informed, at least to some degree, by climate and weather information. Although many farmers indicate that they use seasonal information to make some crop decisions, their responses to this question obscure the extent to which they appear to use the technical forecasts in comparison with other information. We pursue this subject in the following sections.

5.2. Farmers’ expectations for the future MAM 2019 rainfall season

Farmers’ expectations for the MAM rainfall season varied. About 34% stated they expected the rainfall to be greater than a normal MAM season, while another 31% and 13% stated they expected rainfall to be lower than or the same as a normal season, respectively. The remaining 21% did not have an expectation. In total, 79% of farmers (n = 393) formed an expectation, and 66% (n = 328) forecasted conditions that were different from a normal season.

Although the majority of farmers formed an opinion about the future, the main reasons for their expectations differed. Of the 501 farmers we survey, 69% (n = 345) based their expectations primarily on their observations of the weather and climate. Specifically, farmers cited either the recent past conditions (e.g. days to weeks), conditions during the prior OND season, or some notion of longer-term climatic changes (Fig. 3). These responses suggest that farmers project a logic that the past is a primary determinant or reflection of the future. It is also noteworthy that very few farmers based their expectations predominantly on landscape, plant, and animal changes (<1%) and that no farmers identified technical forecasts as the most important factor that influenced their expectations. This is not to say that environmental signs and technical forecasts were not important. They have been shown to be influential elsewhere in Kenya (Luseno et al., 2003; Speranza et al., 2010). Rather, these reasons were not the most important for the farmers we surveyed.

Of the three temporal categories, a plurality of farmers cited the seasonal character of rain during the most recent OND season as the dominant reason for their future expectation (34%; n = 168). Given the relatively small study area (Fig. 1), it is likely these farmers experienced similar rainfall in OND, although local variations would also be present. However, among these farmers who cited the OND season as shaping their expectations, the effect was divided almost equally between expecting more than normal rainfall (13%; n = 67) and below normal rainfall (16%; n = 80). A smaller number expected a normal rainfall amount (4%; n = 21).

Farmers also frequently formed expectations based on their observations of longer-term climate change. In this group, 27% (n = 133) of the farmers referenced changes over many years, including references to “climate change.” This group had about equal numbers expecting above normal (12%; n = 60) and below normal rainfall (11%; n = 56).

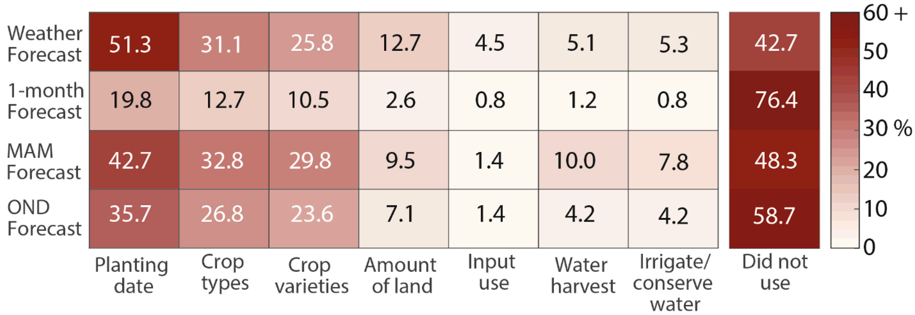

Fig. 2. Percent of farmers who utilize weather and climate forecasts in different farming decisions as well as the percent who do not utilize weather and climate forecasts (right-most column). Black and white text numbers are used to improve visibility.

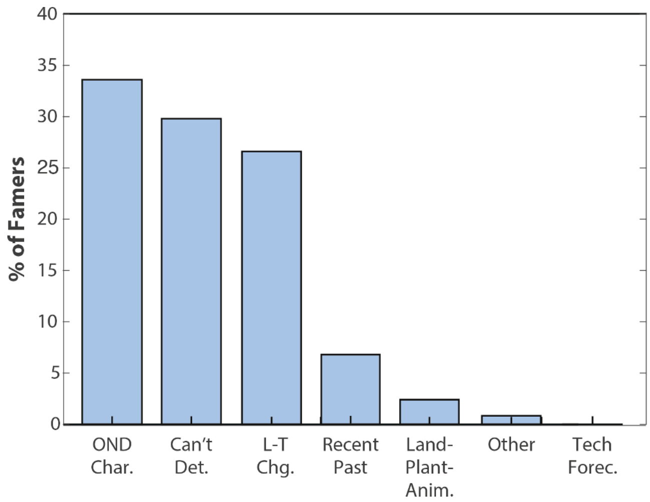

Fig. 3. Reasons farmers create expectations of the upcoming 2019 MAM season. Farmers who provided more than one reason were asked to select the most influential one. Sample size is 500. Labels are as follows: "OND Char" is the Character of rainfall during the OND season; "Can't Det." means Can't Determine; "L-T Chg" relates to weather and climate changes over a long-term period; "Recent Past" relates to weather changes within the previous few weeks to months; "Land-Plant-Anim." relates to changes in the landscape, plants or animal behaviors; "Tech Fore" relates to technical forecasts offered on the radio and TV and originating from organizations like the Kenya Meteorological Service.

5.3. Associations between MAM 2019 expectations and crop decisions

As described above, farmers report that they principally draw on their own observations when developing future rainfall expectations (Fig. 3), although their on-farm decisions are also informed, at least to some extent, by technical information (Fig. 2). Regardless of how farmers form their seasonal expectations, we analyze the associations between a farmer's seasonal expectations and three crucial decisions the farmer makes each crop season: expected seed maturation variety, expected diversification of seed maturation varieties, and expected planting date. We use logistic regression models for those farming decisions with bivariate outcomes (i.e. expected maturation category of maize seeds planted and intention to plant multiple maturation-category seeds) and a linear regression model for the farming decision with a continuous outcome (i.e. expected planting date) to discern relationships between rainfall expectations and farming decisions.

5.3.1. Descriptive statistics of farmer decisions

Table 2 presents descriptive statistics of farming decisions as well as variables describing the seasonal climate expectations. For the 2019 MAM season, farmers on average expected to plant in mid-March (Julian day 74), but the range was large. Some farmers expected to plant as early as mid-February while others as late as mid-May. The majority of farmers expected to plant at least one late-maturing variety, whereas about a third of the farmers expected to plant an early- and/or an intermediate-maturing variety. Nearly a quarter of the sample expected to plant more than one maturity category of seed.

Table 2
Descriptive statistics for farm decisions and farmer expectations of seasonal rainfall, onset, and ability to know the future climate.

Variables	Mean	SD	Range	N
Expected Farming Decisions for MAM 2019				
Early-maturing seed (1 = yes)	0.34	0.48	0–1	501
Intermediate-maturing seed (1 = yes)	0.30	0.46	0–1	501
Late-maturing seed (1 = yes)	0.52	0.50	0–1	501
More than one maturity category of seed (1 = yes)	0.24	0.43	0–1	501
Planting date (Julian day)	74	17	38–141	437
Seasonal Rainfall Expectations for MAM 2019				
Above-normal rainfall (1 = yes)	0.34	0.48	0–1	501
Below-normal rainfall (1 = yes)	0.31	0.46	0–1	501
Same as normal rainfall (1 = yes)	0.13	0.37	0–1	501
Can't determine (1 = yes)	0.21	0.41	0–1	501
Rainfall Onset for MAM 2019				
Expected day of rain onset (Julian day)	89	18	45–172	434
Ability to Know Future Climate				
Change in ability to know future climate (1 = becoming more difficult)	0.79	0.41	0–1	492

5.3.2. Seed maturity selections and seasonal rainfall expectations

Turning now to the relationship between seasonal expectations and farmers' intended decisions, Fig. 4 shows the percent of farmers who expressed each category of seasonal expectations, grouped by their anticipated seed choice. Although each respondent provided only one seasonal expectation, some farmers expected to plant more than one maturing variety. Therefore, the sum of percentages for each seasonal expectation across the three seed maturity choices can be greater than 100%. The asterisks in Fig. 4 denote rates of seasonal expectations that differ significantly from the baseline, "same as normal," group within a given seed choice category, according to logistic regression models that control for relevant individual-, and household-, and community-level attributes (see Supplemental material for full regression results).

The regression analysis identified significant associations between seasonal expectations and the selection of early- and late-maturing seed varieties (Fig. 4; Supplemental material). Around 40% of the farmers who have a below-normal rainfall expectation planned to plant an early-maturing variety, compared with only 20% of farmers who expected normal rainfall (Fig. 4; Supplemental material). This association is intuitive because early-maturing varieties would likely fare better than others during a shorter and/or a drier rainfall season. Similarly, farmers who did not form an expectation about the coming season were also likely to foresee planting an early-maturing variety. This result suggests that these farmers, who are unsure of future precipitation conditions, tend to err on the side of risk aversion by choosing a variety that could perform well even under overall drier conditions.

Late-maturing varieties were the most popular intended seed choice among our respondents and, in particular, among the baseline respondents in our regression model (i.e. those who expect rainfall to be at a normal level, Fig. 4). Nonetheless, in comparison with that baseline, far fewer farmers expected to select a late-maturing variety if they anticipated below-normal rain, and the relative difference (expressed as odds ratios in the Supplemental material) was greatest of all the expectation-variety pairings. Just as it makes intuitive sense for the farmers who cast a "below-normal" forecast to plant short-maturing varieties at high rates, it also makes sense for them not to plant long-maturing varieties at high rates—in a short and/or dry season, late-maturing seed varieties more likely would have lower yields. In contrast, no significant relationships exist between seasonal expectations and the selection of intermediate-maturing varieties (Fig. 4; Supplemental material). In the Supplemental material, we briefly discuss several other relationships between the selection of different maturing varieties and control variables; these relationships show less of an effect of the selection varieties than the farmers' expectations.

Planting more than one maturing variety is a strategy particularly common among farmers who expect above-normal rainfall and among those who did not form a seasonal expectation. They are about two times more likely to plant more than one seed maturity variety than the baseline. Why this approach is less common among those who expect below-normal rainfall warrants further research and explanation. Perhaps the somewhat lower proportion of farmers planting more than one maturing variety in this group is due to their risk aversion and high rates of selecting short-maturing varieties: for these farmers, the potential gains from this approach if rainfall is abundant may be outweighed by the potential losses if the precipitation is low.

Although expected behaviors may be aspirational and may not become reality for a variety of reasons, intention is an important metric for decisions that need to be made well in advance of a specific date. As others have shown, the selection of seed varieties is complicated and influenced by seed availability and other factors such as age, education, perceptions of seed performance, and networks (Waldman et al., 2017). Yet, even if an action does not ultimately occur, the planning can set in motion other activities. That said, we observed positive associations between past actual outcomes and the future expectations reported on here, which provide a measure of credibility that farmers' expectations of future decisions align with what actually occurs. For example, the percent of

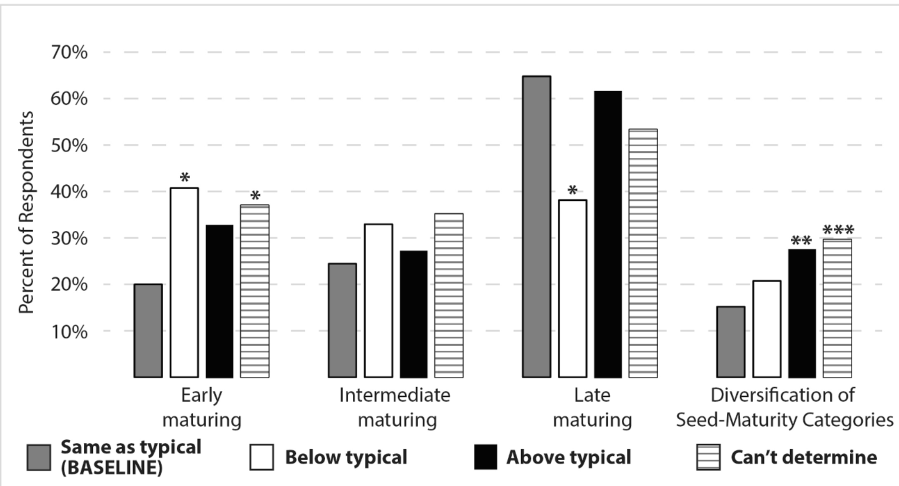

Fig. 4. The percent of respondents who expect to plant different maturing varieties based on their rainfall expectations. Asterisks denote the statistical significance (*5%, **1%, and ***0.1%) of the associations between seed choice and farmer forecast pairing in comparison to the seed choice and baseline forecast pairing, controlling for relevant individual-, and household-, and community-level attributes. The statistical significance is derived from logistic regressions (Supplemental Material).

farmers who planted more than one variety in the 2018 OND season and who expected to plant more than one variety in 2019 MAM were similar, about 21% compared to 24%, respectively. Additionally, the relationship between the actual sowing date and seed maturity variety planted in the 2018 MAM season was not significant, a result we also found for MAM 2019.

5.3.3. *Planting dates and seasonal rainfall expectations*

Farmers expected to plant maize for the MAM seasonal rains as early as mid-February and as late as mid-May (Table 2, Fig. 5). However, as evident in Fig. 5, expected planting date bore no meaningful associations with seasonal expectations in a linear regression model (results not presented). In fact, the range of expected planting dates is broad, spanning nearly the entire season, and there is overlap in the interquartile range of expected planting dates in all four categories of seasonal expectation (Fig. 5a). Surprisingly, the expected planting date also was unassociated with the seed maturity category in the linear regression model (results not presented). We had hypothesized that farmers would expect to plant their late-maturing varieties earlier in the year, and earlier-maturing varieties anytime in the year. However, the median and interquartile range of Julian dates for the groups who expect to plant an early-, intermediate-, and late-maturing seed varieties are nearly identical (Fig. 5b). These results can be further visualized in Fig. 5c where there are no clear patterns between the expected rain onset and choice of seed maturation category (designated by different colors on Fig. 5c). While the similarity among these planting date distributions is partially caused by 24% of the farmers expecting to plant seeds with different maturing periods, the disconnect between expectations of planting date and different maturing seed varieties was also observed in the 2018 MAM season. These results suggest that the timing of planting is influenced more by other factors than variety and rainfall such as, for example, adherence to a static planting calendar.

Farmers could also decide when to plant as the weather unfolds, and there is evidence for this in our data. As evidenced by the concentration of points beneath the y = x line, the expected onset tends to precede expected planting date by one or more week (Fig. 5c). This result suggests that farmers wait for the rains to begin before planting maize, and further supports the notion that expectations of rainfall made months in advance do not directly influence planting dates.

6. Discussion

In comparing expectations of MAM and OND rainfall, farmers utilize MAM forecasts to a higher degree (Fig. 2). This likely relates to the greater significance of the MAM season for maize cultivation. MAM is not only a longer, wetter growing season, but it is also the season in which more farmers grow maize. Only 2% percent of the farmers did not plant maize in MAM 2018, whereas approximately

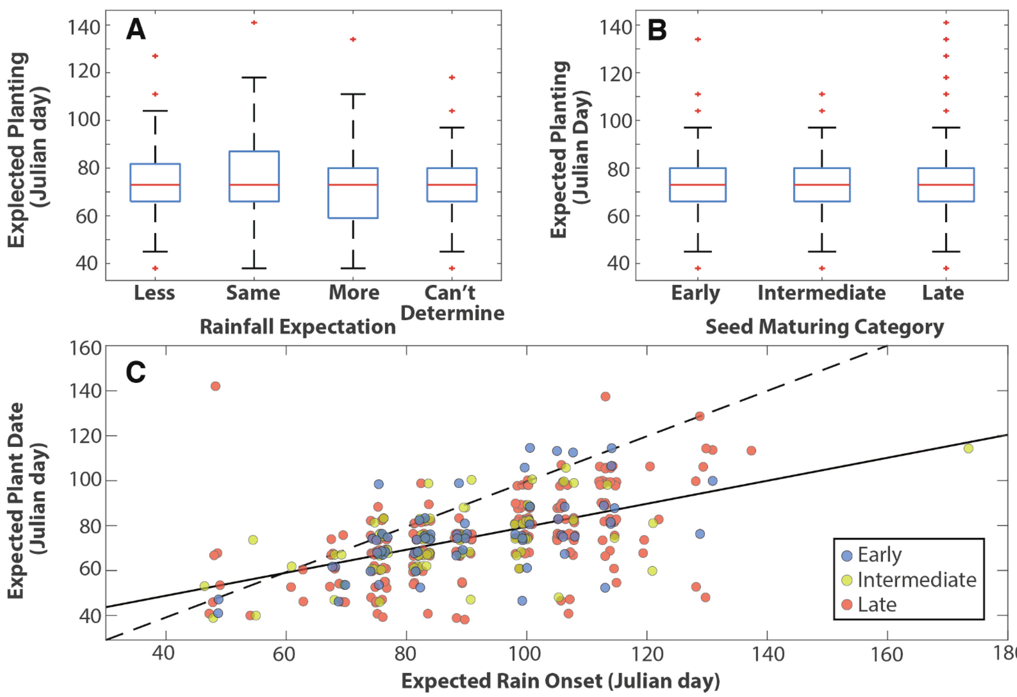

Fig. 5. (a) The expected planting Julian day by the four different expectations of MAM 2019 rainfall. (b) The expected planting day and expected onset day for farmers who expect to plant different maturing seeds. In both (a) and (b), the central mark of each box represents the median, the box edges denote the 25th and 75th percentiles, the whiskers extend to the most extreme value not considered two standard deviations from the mean, and the crosses are outliers. (c) The expected MAM onset (Julian day) and expected planting day for different maturing seed varieties. Values are calculated to the nearest week. Overlapping points are slightly offset for visual display. The dotted line is the x = y line; the solid line is the best fit of all data.

50% of the sample did not plant maize in the OND 2018 season.

This analysis also identifies important associations between farmers' agricultural decisions and their seasonal expectations. For the MAM season, different expectations of rainfall had instrumental effects on some, but not all, types of planting decisions we studied. Farmers expecting below-normal seasonal rain exhibit high likelihood of expecting to plant early-maturing varieties (Fig. 4; Supplemental material), representing a planting strategy with low risks and low rewards. Farmers making an above-normal forecast have a high likelihood of expecting to plant more than one type of seed maturity. And farmers who did not form an expectation of seasonal rainfall exhibit high likelihood both of expecting to plant early-maturing varieties and of expecting to plant varieties with several maturation periods. These results provide evidence that farmer expectations of future conditions affect important agricultural decisions. On the other hand, there were no associations between expectations of future seasonal climate and anticipated planting date (Fig. 5).

Our results provide important insights. First, seasonal expectations appear to influence strategic decisions on the maturity type and diversity of seeds and less so on tactical decisions about when to plant. Strategic decisions require advanced planning, whereas tactical decisions are more responsive to emergent conditions. Second, a plurality of farmers bases their future expectations of seasonal rainfall on the past season's rainfall. However, because each season is quasi-independent, the past is not a good guide for the future, and this logic may lock farmers into poor decisions. Finally, we offer some explanations of why farmers base their predictions on past conditions.

6.1. Risk management: strategic and tactical farm management decisions and their tradeoffs

That seasonal rainfall expectations appear to inform decisions related to seed maturation type but not planting dates highlights how some decisions align better than others with seasonal climate information, notably ex-post risk management decisions. Because maize matures over the course of multiple months and requires rainfall throughout the growing season, seed varieties are in part selected based on an idea of an entire growing season. A rainfall forecast in the next seven days would be inadequate to decide on a variety for planting. On the other hand, a weather forecast may be adequate to decide on the day of planting, whereas an expectation for the entire season appears not to be. The planting sensitivity to rain onset is also seen among farmers who expected to plant around the same time or shortly before they expected the rains to begin (Fig. 5c). This is a type of in-season risk management and is crucial for rainfed crops. Farmers who plant too early, risk the failed germination of seeds from insufficient soil moisture, while farmers who plant too late, risk having their seeds wash away during intense rains (Fisher et al., 2015). This type of weather adjustment is consistent with observations of smallholder farming systems elsewhere. In Lesotho, for example, Ziervogel et al. (2005) found that farmers use forecasts mostly for short-term, immediate decisions such as sowing fewer crops and choosing when to plant. And in Uganda, (Orlove et al., 2010) showed that farmers often make decisions in an improvised and iterative sequence of adjustments rather than following a discrete management plan.

There are consequences to making decisions in advance that do not afford flexibility as climate and weather conditions evolve. As one potential example among the farmers we surveyed, farmers who expect dry conditions are more likely to obtain an early-maturing variety (Fig. 4; Supplemental material). If these farmers acquired only this seed in advance of planting, they become locked into this one choice. While an early-maturing variety yields a safer outcome, it also prevents farmers from capitalizing on conditions more favorable for late-maturing varieties. Having the ability to plant different maturing varieties, then, would enable more choices when tactical decisions are made.

6.2. A lack of seasonal rainfall correlation leads to fortuitous outcomes

Because farmers make decisions based on their expectations of the future, we examine if the underlying logic is borne out by the observational data. We compared farmers' perceptions of above- and below- normal with seasonal rainfall anomalies calculated over

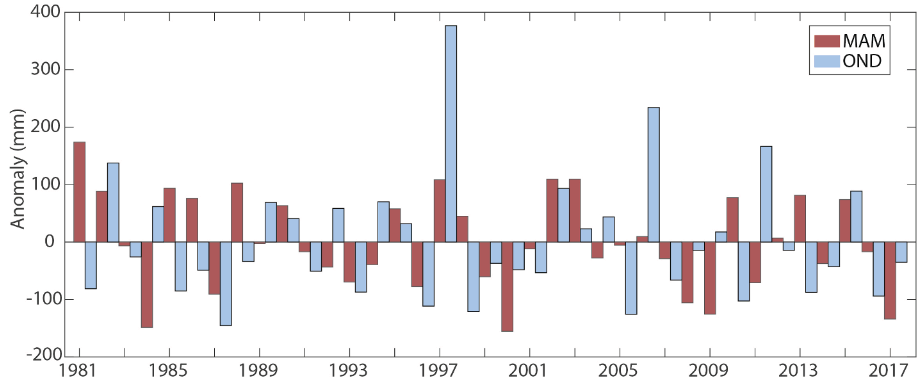

Fig. 6. Seasonal rainfall anomalies. Data source is CHIRPS monthly data (Funk et al., 2014). Precipitation values represent the average of 20 grids that encompass the study site.

the entire study site using Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Funk et al., 2014). We were unable to standardize farmers' understanding of above- and below-normal with the observational data. We are thus cautious not to overinterpret the following results.

Fig. 6 shows a time-series of deviations from average for the MAM and OND rainfall averaged across the study site. A forecast for seasonal persistence—when back-to-back seasons are both positive or negative—occurs roughly 57% of the time, while a forecast for total rainfall switching from above to below average occurs the other 43% of the time. Although this record is relatively short, the seasonal autocorrelation for the two categories is not significant, further emphasizing seasonally independent outcomes. For the plurality of farmers who base their expectations on the previous season, roughly 33% of our sample, the quasi-independence of each season means that farmers are only accidentally correct, if they are correct at all.

The lack of seasonal autocorrelation can be explained by the different physical mechanisms that drive rainfall in each season. Nicholson (2017) reviewed the East African rainfall climatology to show a complex setting where both local and global dynamics influence each season in different configurations. For the OND rains, the sea surface temperatures in the Pacific and Indian Oceans, the east-west surface winds, and the 200 mbar winds over the central equatorial Indian Ocean are interdependent and play roles in generating rainfall. Moreover, the strength of these links and the degree of influence of any individual condition change through time. On the other hand, each month of the MAM period shows little mutual correlation because the causal factors and teleconnections are markedly different in each month (Nicholson, 2017).

While decisions underpinned by a seasonal correlation logic may be only fortuitous, there appears to be no more skillful alternative for MAM at the moment. Technical SCFs are created by the KMD and the WMO regional climate center. However, the MAM forecasts have low skill (Nicholson, 2017). In fact, the 2018 MAM SCFs gave increased odds for below-normal rainfall for most of Kenya, while in actuality the rainfall was above-normal for the majority of the measuring stations; for some locations, there was even record-setting rainfall and severe flooding. And while it is tempting to see some of the farmers' expectations as fairly accurate (e.g. 57% of the time the preceding season has the same anomaly as the current season), even one poor crop can be severely damaging to the livelihoods of marginal farmers.

6.3. Explanations for a seasonal heuristic

Our results suggest that many farmers base their expectations of upcoming seasonal rainfall mainly on their observations and memories of past rainfall. However, farmers may be drawing on information obtained from a variety of sources that we were unable to account for (Grothmann and Patt, 2005; Washington and Downing, 1999). We therefore discuss three confounding factors specific to our study location that could inform Kenyan farmers' expectations of seasonal rainfall: 1) personal experiences and mental models, 2) perceived credibility and legitimacy of weather and climate information, and 3) perceptions that predicting the future is becoming more difficult.

Farmers' experiences with rainfall variability influence their perceptions of the future weather and climate. Their beliefs are often formed by accessing memories that are most available to them, a function of both recency and impact. The more recently people experience a shock or disturbance, the higher they judge its probability to recur (Hertwig et al., 2004; Tversky and Kahneman, 1974). That consecutive seasons of severe drought in 2011 and 2016 occurred in Kenya that caused severe food insecurity (Nicholson, 2014b; Uhe et al., 2018) potentially explains why many farmers perceive one season to be a harbinger for the next. These events could have etched into the memories of some farmers a heuristic of seasonal persistence. On the other hand, heavy rains and flooding in MAM of 2018 were followed by a drier-than-average OND 2018 season. This pattern may have had the opposite effect for some people. The opposing ways that the farmers used the prior season to inform their expectations point to the potential for individual experiences to lead to differing conclusions about future risk (Howe et al., 2015).

Perceptions of the credibility and legitimacy of information also influence how individuals process information (Bryant and Oliver, 2009; Gamson and Modigliani, 2002; Scheufele and Tewksbury, 2007). Individuals' perceptions can be influenced by media presentation of information, how much information is consumed (Zucker, 2017), influential leaders (Katz et al., 2017), and social networks (Ziervogel and Downing, 2004). Trust in both the informational content and its messenger is important. Among the farmers we surveyed, there were differing levels of trust in one's forecasting ability and in external sources of weather and climate information. Generally, farmers stated they have high or moderate trust in their own weather and climate forecasts, and lower trust in the weather and climate information communicated by radio, TV, extension officers, and community leaders. Past failed forecasts may have contributed to lower perceptions of trust in externally-sourced forecasts. In 2018, both KMD and the media did not forecast extremely high rainfall in MAM and the drier-than-average OND season. Other faulty forecasts may also have happened in the past given that forecast skill for the MAM season in Kenya is low (Nicholson, 2014a).

Finally, there is a growing sense among the farmers that climate change is eroding their ability to forecast the future. The vast majority of the farmers we surveyed, 79%, stated it is becoming more difficult for them to predict the future rains (Table 1), and they overwhelmingly attribute this difficulty to climate change. While this feeling does not yet appear to deter farmers from making a prediction—only 21% did not form an expectation of the MAM season (Table 1)—farmers could be altering their behaviors in ways we did not capture in our survey. They may also alter their activities in the future. On the one hand, farmers could seek more information from additional sources to counteract their growing uncertainty. In this case, farmers may increase their use of technical forecasts, consult more with extension officers, and/or solicit advice from trusted community members. On the other hand, continued uncertainty may undermine farmers' confidence in and use of all forms of forecasts. Of the 43% of farmers who did not use technical weather forecasts (Fig. 2), about 46% of them stated a lack of accuracy as a main reason.

7. Implications for climate resilience activities

National governments and some of the largest donors and science consortia like the World Bank, the Consultative Group on International Agricultural Research (CGIAR), and the WMO have invested heavily in programs that improve access, understanding, and use of climate information at seasonal or longer timescales (Vaughan and Dessai, 2014). Climate-smart agriculture and the Global Framework for Climate Services are two such examples (Lipper et al., 2014; World Meteorological Organization, 2011). In 2014 alone, more than US$24B was spent on climate information services globally, close to the amount spent on weather services that focus on the provision of near real-time information (Georgeson et al., 2017). In theory, accurate weather forecasts allow for in-season risk management strategies like adjustments to sowing dates, while seasonal forecasts enable ex-ante risk management decisions like choices of crop varieties and types (Millner and Washington, 2011). By way of conclusion, we consider the contribution of our findings to the theory and practice of climate resilience-building activities.

Our results suggest there are benefits in understanding the links between farmers expectations of future climate and their management strategies. On the one hand, farmers develop heuristics relating rainfall expectations to seed choice behaviors. This manifests as an apparent underestimation of seasonal climate uncertainty whereby most farmers plan to plant only one seed maturing variety. This decision may be influenced by farmers' relatively high confidence in their own forecasts. And yet, the complex and changing interactions of multiple climate processes (e.g. sea surface temperatures in the Pacific Ocean) as well as the observations suggest rainfall in OND and MAM should be considered independent. A more flexible management approach that can accommodate several possible outcomes would avoid locking in decisions based on conditions that don't ultimately manifest. Climate resilience activities that explore connections between expectations and actions would therefore have recourse to tailor capacity building interventions that are in tune with adaptive management approaches.

In addition, rainfall expectations may be a key determinant of seed choice behaviors, and there may be a consistency to farmers' expectations if their underlying rationales remain stable through time. In this case, knowledge of the expectations could reveal outcomes by suggesting choices that can either amplify or dampen risk. More research is needed, however, on the stability of farmers' rationales through time. Climate resilience initiatives with a research component could investigate this dimension in the process of monitoring and evaluation of climate service interventions.

Our results also suggest a need to improve climate literacy in order to create a larger foundation from which information intensive tools can be evaluated and incorporated by farmers. Often, the production of climate science for decision making in the developing world is focused on end-of-the-line products like SCFs. However, these products require users to have a high degree of technical expertise in order to understand them and make informed judgements on their utility. In many cases, that expertise is lacking, and the products can be black-boxes to users, essentially requiring farmers to trust the information if they decide to use it.

In recent years, climate services have adopted a "co-production" model (World Meteorological Organization, 2011), which has helped lead to more participatory forms of climate and weather information capacity building (Dayamba et al., 2018; Guido et al., 2019; Loboguerrero et al., 2018). While these efforts help, there are still many examples where users of climate and weather information do not understand the products. Indeed, better understanding users' knowledge gaps is a pressing component of a climate service-learning agenda (Carr et al., 2019).

Building on participatory climate services activities, we suggest incorporating discussions on how the climate system works. In this sense, education around climate dynamics is treated in a similar way as a SCF, namely as a climate service "product". Additionally, we suggest that the discussions should bring to the fore and challenge farmers' assumptions about the links between their management practices and the climate. Discussions, as opposed to prescriptive forms of information transfer, would give farmers the ability to decide which tools and information is most valuable to them. However, much like the development of technical information, participatory training requires a set of skills in order to be executed effectively (Porter and Dessai, 2017).

Finally, as new weather and climate technologies become available, we need to reflect on what the psychological implications of this transformation are for farmer resilience. While in theory technological advances should improve farmer decision-making, there are numerous logistical and psychological barriers. We have highlighted a few here, emphasizing the need to understand farmer biases related to weather (Waldman et al., 2019) and the relationship between farmer perceptions and observational data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are indebted to the many farmers who shared their ideas and time, often in lieu of tending their farms. We especially thank John Gitonga and Boniface Kimathi from the Mpala Research Centre in Nanyuki, Kenya for research coordination and feedback on analysis. This research was funded by the U.S. National Science Foundation, grant number SES-1360463.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2020.100247.

References

Adger, W.N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D.R., Naess, L.O., Wolf, J., Wreford, A., 2009. Are there social limits to adaptation to climate change? Clim. Change. https://doi.org/10.1007/s10584-008-9520-z.

Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A.J., Morales, C., 2015. The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. Food Security 7, 303–321. https://doi.org/10.1007/s12571-015-0446-9.

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., Herrero, M., 2013. Adapting agriculture to climate change in Kenya: household strategies and determinants. J. Environ. Manage. 114, 26–35. https://doi.org/10.1016/J.JENVMAN.2012.10.036.

Bryant, J., Oliver, M.B. (Eds.), 2009. Media Effects: Advances in Theory and Research. Routledge.

Cairns, J.E., Hellin, J., Sonder, K., Araus, J.L., MacRobert, J.F., Thierfelder, C., Prasanna, B.M., 2013. Adapting maize production to climate change in sub-Saharan Africa. Food Security. https://doi.org/10.1007/s12571-013-0256-x.

Camberlin, P., Boyard-Micheau, J., Philippon, N., Baron, C., Leclerc, C., Mwongera, C., 2014. Climatic gradients along the windward slopes of Mount Kenya and their implication for crop risks. Part 1: climate variability. Int. J. Climatol. 34, 2136–2152. https://doi.org/10.1002/joc.3427.

Carr, E.R., Goble, R., Rosko, H.M., Vaughan, C., Hansen, J., 2019. Identifying climate information services users and their needs in Sub-Saharan Africa: a review and learning agenda. Clim. Develop. 1–19 https://doi.org/10.1080/17565529.2019.1596061.

Carr, E.R., Onzere, S.N., 2017. Really effective (for 15% of the men): Lessons in understanding and addressing user needs in climate services from Mali. Clim. Risk Manage. https://doi.org/10.1016/J.CRM.2017.03.002.

Carr, E.R., Owusu-Daaku, K.N., 2016. The shifting epistemologies of vulnerability in climate services for development: the case of Mali's agrometeorological advisory programme. Area 48, 7–17. https://doi.org/10.1111/area.12179.

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B., Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? Agric. Ecosyst. Environ. 126, 24–35. https://doi.org/10.1016/j.agee.2008.01.007.

Crane, T.A., Roncoli, C., Paz, J., Breuer, N., Broad, K., Ingram, K.T., Hoogenboom, G., 2009. Forecast skill and farmers' skills: seasonal climate forecasts and agricultural risk management in the southeastern United States. Weather Clim. Soc. 2, 44–59. https://doi.org/10.1175/2009wcas1006.1.

Dayamba, D.S., Ky-Dembele, C., Bayala, J., Dorward, P., Clarkson, G., Sanogo, D., Diop Mamadou, L., Traoré, I., Diakité, A., Nenkam, A., Binam, J.N., Ouedraogo, M., Zougmore, R., 2018. Assessment of the use of Participatory Integrated Climate Services for Agriculture (PICSA) approach by farmers to manage climate risk in Mali and Senegal. Clim. Serv. https://doi.org/10.1016/j.cliser.2018.07.003.

Dilling, L., Lemos, M.C., 2011. Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. Global Environ. Change 21, 680–689. https://doi.org/10.1016/j.gloenvcha.2010.11.006.

Eakin, H.C., Lemos, M.C., Nelson, D.R., 2014. Differentiating capacities as a means to sustainable climate change adaptation. Global Environ. Change 27, 1–8. https://doi.org/10.1016/J.GLOENVCHA.2014.04.013.

Ericksen, P., Said, M., Leeuw, J. de, Silvestri, S., Zaibet, L., Kifugo, S., Sijmons, K., Kinoti, J., Ng'ang'a, L., Landsberg, F., Stickler, M., 2011. Mapping and valuing ecosystem services in the Ewaso Ng'iro Watershed. Nairobi.

FAOSTAT, 2019. Statistical databases and data-sets of the Food and Agriculture Organization of the United Nations. [WWW Document].

Fisher, M., Abate, T., Lunduka, R.W., Asnake, W., Alemayehu, Y., Madulu, R.B., 2015. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: determinants of adoption in eastern and southern Africa. Clim. Change 133, 283–299. https://doi.org/10.1007/s10584-015-1459-2.

Funk, C.C., Peterson, P.J., Landsfeld, M.F., Pedreros, D.H., Verdin, J.P., Rowland, J.D., Romero, B.E., Husak, G.J., Michaelsen, J.C., Verdin, A.P., 2014. A quasi-global precipitation time series for drought monitoring. U.S. Geol. Survey Data Series 832 4.

Gamson, W.A., Modigliani, A., 2002. Media discourse and public opinion on nuclear power: a constructionist approach. Am. J. Sociol. 95, 1–37. https://doi.org/10.1086/229213.

Georgeson, L., Maslin, M., Poessinouw, M., 2017. Global disparity in the supply of commercial weather and climate information services. Sci. Adv. 3, e1602632 https://doi.org/10.1126/sciadv.1602632.

Gichuki, F.N., Liniger, H., MacMillan, L.C., Schwilch, G., Gikonyo, J.K., 1998. Scarce water: exploring resource availability, use and improved management. Eastern Southern Africa Geogr. J. 8, 16–27.

Glantz, M., 1977. The value of a long-range weather forecast for the west African Sahel. Bull. Am. Meteorol. Soc. 58, 150–158. https://doi.org/10.1175/1520-0477(1977)058<0150:TVOALR>2.0.CO;2.

Gower, D.B., Dell'Angelo, J., McCord, P.F., Caylor, K.K., Evans, T.P., 2016. Modeling ecohydrological dynamics of smallholder strategies for food production in dryland agricultural systems. Environ. Res. Lett. 11, 115005 https://doi.org/10.1088/1748-9326/11/11/115005.

Grothmann, T., Patt, A., 2005. Adaptive capacity and human cognition: the process of individual adaptation to climate change. Global Environ. Change 15, 199–213. https://doi.org/10.1016/j.gloenvcha.2005.01.002.

Guido, Z., Knudson, C., Campbell, D., Tomlinson, J., 2019. Climate information services for adaptation: what does it mean to know the context? Clim. Develop. https://doi.org/10.1080/17565529.2019.1630352.

Guido, Z., Knudson, C., Finan, T., Madajewicz, M., Rhiney, K., 2020. Shocks and cherries: the production of vulnerability among smallholder coffee farmers in Jamaica. World Dev. 132, 104979 https://doi.org/10.1016/j.worlddev.2020.104979.

Hassan, R., Nhemachena, C., 2008. Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis. AfJARE 2. https://doi.org/10.4135/9781452243733.

Hastenrath, S., Polzin, D., Mutai, C., Hastenrath, S., Polzin, D., Mutai, C., 2011. Circulation mechanisms of kenya rainfall anomalies. J. Clim. 24, 404–412. https://doi.org/10.1175/2010JCLI3599.1.

Hertwig, R., Barron, G., Weber, E.U., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol. Sci. 15, 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x.

Howe, P.D., Mildenberger, M., Marlon, J.R., Leiserowitz, A., 2015. Geographic variation in opinions on climate change at state and local scales in the USA. Nat. Clim. Change 5, 596–603. https://doi.org/10.1038/nclimate2583.

Ingram, K.T., Roncoli, M.C., Kirshen, P.H., 2002. Opportunities and constraints for farmers of west Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. Agric. Syst. 74, 331–349. https://doi.org/10.1016/S0308-521X(02)00044-6.

Jayne, T.S., Mather, D., Mghenyi, E., 2010. Principal challenges confronting smallholder agriculture in Sub-Saharan Africa. World Dev. 38, 1384–1398. https://doi.org/10.1016/j.worlddev.2010.06.002.

Katz, E., Lazarsfeld, P.F., Roper, E., 2017. Personal Influence: The Part Played by People in the Flow of Mass Communications. Routledge.

Knight, J., Weir, S., Woldehanna, T., 2003. The role of education in facilitating risk-taking and innovation in agriculture. J. Develop. Stud. 39, 1–22.

Krell, N.T., Giroux, S.A., Guido, Z., Hannah, C., Lopus, S.E., Caylor, K.K., Evans, T.P., 2020. Smallholder farmers' use of mobile phone services in central Kenya. Clim. Develop. 1–13 https://doi.org/10.1080/17565529.2020.1748847.

Kunreuther, H., Weber, E.U., 2014. Aiding decision making to reduce the impacts of climate change. J. Consum. Policy 37, 397–411. https://doi.org/10.1007/s10603-013-9251-z.

Liebmann, B., Hoerling, M.P., Funk, C., Bladé, I., Dole, R.M., Allured, D., Quan, X., Pegion, P., Eischeid, J.K., 2014. Understanding recent eastern Horn of Africa rainfall variability and change. J. Clim. 27, 8630–8645. https://doi.org/10.1175/JCLI-D-13-00714.1.

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Sen, P.T., Sessa, R., Shula, R., Tibu, A., Torquebiau, E.F., 2014. Climate-smart agriculture for food security. Nat. Clim. Change. https://doi.org/10.1038/nclimate2437.

Loboguerrero, A.M., Boshell, F., León, G., Martinez-Baron, D., Giraldo, D., Recaman Mejía, L., Díaz, E., Cock, J., 2018. Bridging the gap between climate science and farmers in Colombia. Clim. Risk Manage. 22, 67–81. https://doi.org/10.1016/j.crm.2018.08.001.

Lopus, S., McCord, P., Gower, D., Evans, T., 2017. Drivers of farmer satisfaction with small-scale irrigation systems. Appl. Geogr. 89, 77–86. https://doi.org/10.1016/j.apgeog.2017.10.004.

Luseno, W.K., McPeak, J.G., Barrett, C.B., Little, P.D., Gebru, G., 2003. Assessing the value of climate forecast information for pastoralists: evidene from Southern Ethiopia and Northern Kenya. World Dev. 31, 1477–1494. https://doi.org/10.1016/S0305-750X(03)00113-X.

Lyon, B., Dewitt, D.G., 2012. A recent and abrupt decline in the East African long rains. Geophys. Res. Lett. 39, n/a-n/a. https://doi.org/10.1029/2011GL050337.

McCord, P., Dell'Angelo, J., Gower, D., Caylor, K.K., Evans, T., 2017. Household-level heterogeneity of water resources within common-pool resource systems. Ecol. Soc. 22, art48. https://doi.org/10.5751/es-09156-220148.

McCord, P.F., Cox, M., Schmitt-Harsh, M., Evans, T., 2015. Crop diversification as a smallholder livelihood strategy within semi-arid agricultural systems near Mount Kenya. Land Use Policy 42, 738–750. https://doi.org/10.1016/j.landusepol.2014.10.012.

Meijer, S.S., Catacutan, D., Ajayi, O.C., Sileshi, G.W., Nieuwenhuis, M., 2015. The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. Int. J. Agric. Sustain. 13, 40–54. https://doi.org/10.1080/14735903.2014.912493.

Millner, A., Washington, R., 2011. What determines perceived value of seasonal climate forecasts? A theoretical analysis. Global Environ. Change 21, 209–218.

Mugo, R.M., Ininda, J., Okoola, R., 2016. Inter annual variability of onset and cessation of the long rains in Kenya. J. Meteorol. Rel. Sci. 9, 30–47. https://doi.org/10.20987/jmrs.3.05.2016.

Mumo, L., Yu, J., Fang, K., 2018. Assessing impacts of seasonal climate variability on maize yield in Kenya. Int. J. Plant Prod. 12, 297–307. https://doi.org/10.1007/s42106-018-0027-x.

Nicholson, S.E., 2018. The ITCZ and the seasonal cycle over equatorial Africa. Bull. Am. Meteorol. Soc. 99, 337–348. https://doi.org/10.1175/BAMS-D-16-0287.1.

Nicholson, S.E., 2017. Climate and climatic variability of rainfall over eastern Africa. Rev. Geophys. 55, 590–635. https://doi.org/10.1002/2016RG000544.

Nicholson, S.E., 2015. Long-term variability of the East African "short rains" and its links to large-scale factors. Int. J. Climatol. 35, 3979–3990. https://doi.org/10.1002/joc.4259.

Nicholson, S.E., 2014a. The predictability of rainfall over the greater horn of Africa. Part I: prediction of seasonal rainfall. J. Hydrometeorol. 15, 1011–1027. https://doi.org/10.1175/JHM-D-13-062.1.

Nicholson, S.E., 2014b. A detailed look at the recent drought situation in the Greater Horn of Africa. J. Arid Environ. 103, 71–79. https://doi.org/10.1016/j.jaridenv.2013.12.003.

Nkiaka, E., Taylor, A., Dougill, A.J., Antwi-Agyei, P., Fournier, N., Bosire, E.N., Konte, O., Lawal, K.A., Mutai, B., Mwangi, E., Ticehurst, H., Toure, A., Warnaars, T., 2019. Identifying user needs for weather and climate services to enhance resilience to climate shocks in sub-Saharan Africa. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab4dfe.

Ogalleh, S.A., Vogl, C.R., Eitzinger, J., Hauser, M., 2012. Local perceptions and responses to climate change and variability: the case of Laikipia District, Kenya. Sustainability 4, 3302–3325. https://doi.org/10.3390/su4123302.

Ogallo, L., Bessemoulin, P., Ceron, J.-P., Mason, S., Connor, S.J., 2008. Adapting to climate variability and change: the Climate Outlook Forum process. WMO Bull.

Orlove, B., Roncoli, C., Kabugo, M., Majugu, A., 2010. Indigenous climate knowledge in southern Uganda: the multiple components of a dynamic regional system. Clim. Change 100, 243–265. https://doi.org/10.1007/s10584-009-9586-2.

Orlove, B.S., Chiang, J.C.H., Cane, M.A., 2000. Forecasting Andean rainfall and crop yield from the influence of El Nino on Pleiades visibility. Nature 403, 68–71. https://doi.org/10.1038/47456.

Paul, C.J., Weinthal, E.S., Bellemare, M.F., Jeuland, M.A., 2016. Social capital, trust, and adaptation to climate change: evidence from rural Ethiopia. Global Environ. Change 36, 124–138. https://doi.org/10.1016/j.gloenvcha.2015.12.003.

Porter, J.J., Dessai, S., 2017. Mini-me: why do climate scientists' misunderstand users and their needs? Environ. Sci. Policy 77, 9–14. https://doi.org/10.1016/j.envsci.2017.07.004.

Rahm, M.R., Huffman, W.E., 1984. The adoption of reduced tillage: the role of human capital and other variables. Am. J. Agric. Econ. 66, 405–413. https://doi.org/10.2307/1240918.

Ray, D.K., Gerber, J.S., Macdonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6, 5989. https://doi.org/10.1038/ncomms6989.

Ray, D.K., Ramankutty, N., Mueller, N.D., West, P.C., Foley, J.A., 2012. Recent patterns of crop yield growth and stagnation. Nat. Commun. 3, 1293. https://doi.org/10.1038/ncomms2296.

Rockström, J., Barron, J., Fox, P., 2002. Rainwater management for increased productivity among small-holder farmers in drought prone environments. Phys. Chem. Earth 27, 949–959. https://doi.org/10.1016/S1474-7065(02)00098-0.

Roncoli, C., Ingram, K., Kirshen, P., 2002. Reading the rains: local knowledge and rainfall forecasting in Burkina Faso. Soc. Nat. Resour. 15, 409–427. https://doi.org/10.1080/08941920252866774.

Roudier, P., Muller, B., D'Aquino, P., Roncoli, C., Soumaré, M.A., Batté, L., Sultan, B., 2014. The role of climate forecasts in smallholder agriculture: lessons from participatory research in two communities in Senegal. Clim. Risk Manage. 2, 42–55. https://doi.org/10.1016/j.crm.2014.02.001.

Scheufele, D.A., Tewksbury, D., 2007. Framing, agenda setting, and priming: the evolution of three media effects models. J. Commun. https://doi.org/10.1111/j.0021-9916.2007.00326.x.

Scoones, I., 1998. Sustainable rural livelihoods a framework for analysis. Analysis 72, 1–22. https://doi.org/10.1057/palgrave.development.1110037.

Sheffield, J., Wood, E.F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., Demuth, S., Ogallo, L., 2014. A drought monitoring and forecasting system for sub-sahara african water resources and food security. Bull. Am. Meteorol. Soc. 95, 861–882. https://doi.org/10.1175/BAMS-D-12-00124.1.

Shiferaw, B., Smale, M., Braun, H.J., Duveiller, E., Reynolds, M., Muricho, G., 2013. Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security. Food Secur. 5, 291–317. https://doi.org/10.1007/s12571-013-0263-y.

Shongwe, M.E., van Oldenborgh, G.J., van den Hurk, B., van Aalst, M., 2011. Projected changes in mean and extreme precipitation in Africa under global warming. Part II: East Africa. J. Clim. 24, 3718–3733. https://doi.org/10.1175/2010JCLI2883.1.

Slovic, P., Peters, E., 2006. Risk perception and affect. Curr. Direct. Psychol. Sci. 15, 322–325. https://doi.org/10.1111/j.1467-8721.2006.00461.x.

Smale, M., Jayne, T.S., 2004. Maize breeding in East and Southern Africa, 1900–2000. 2020 vision briefs.

Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. Global Environ. Change 16, 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008.

Speranza, C.I., Kiteme, B., Ambenje, P., Wiesmann, U., Makali, S., 2010. Indigenous knowledge related to climate variability and change: Insights from droughts in semi-arid areas of former Makueni District, Kenya. Clim. Change 100, 295–315. https://doi.org/10.1007/s10584-009-9713-0.

Tall, A., Coulibaly, J.Y., Diop, M., 2018. Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: implications for Africa. Clim. Serv. https://doi.org/10.1016/j.cliser.2018.06.001.

Tongruksawattana, S., 2014. Climate shocks and choice of adaptation strategy for Kenyan maize-legume farmers: insights from poverty, food security and gender perspectives. Mexico City.

Tschakert, P., Sagoe, R., Ofori-Darko, G., Codjoe, S.N., 2010. Floods in the Sahel: an analysis of anomalies, memory, and anticipatory learning. Clim. Change 103, 471–502. https://doi.org/10.1007/s10584-009-9776-y.

Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. Science (New York, N.Y.) 185, 1124–31. https://doi.org/10.1126/science.185.4157.1124.

Uhe, P., Philip, S., Kew, S., Shah, K., Kimutai, J., Mwangi, E., van Oldenborgh, G.J., Singh, R., Arrighi, J., Jjemba, E., Cullen, H., Otto, F., 2018. Attributing drivers of the 2016 Kenyan drought. Int. J. Climatol. 38, e554–e568. https://doi.org/10.1002/joc.5389.

Ulrich, A., Ifejika Speranza, C., Roden, P., Kiteme, B., Wiesmann, U., Nüsser, M., 2012. Small-scale farming in semi-arid areas: livelihood dynamics between 1997 and 2010 in Laikipia, Kenya. J. Rural Stud. 28, 241–251. https://doi.org/10.1016/J.JRURSTUD.2012.02.003.

UNESCO, 2019. Indigenous Knowledge and Climate Change [WWW Document]. URL: https://en.unesco.org/links (accessed 7.12.19).

Vaughan, C., Dessai, S., 2014. Climate services for society: origins, institutional arrangements, and design elements for an evaluation framework. Wiley Interdiscip. Rev. Clim. Change 5, 587–603. https://doi.org/10.1002/wcc.290.

Waldman, K.B., Blekking, J.P., Attari, S.Z., Evans, T.P., 2017. Maize seed choice and perceptions of climate variability among smallholder farmers. Global Environ. Change 47, 51–63. https://doi.org/10.1016/j.gloenvcha.2017.09.007.
Waldman, K.B., Vergopolan, N., Attari, S.Z., Sheffield, J., Estes, L.D., Caylor, K.K., Evans, T.P., 2019. Cognitive biases about climate variability in smallholder farming systems in Zambia. Weather Clim. Soc. 11, 369–383. https://doi.org/10.1175/wcas-d-18-0050.1.
Washington, R., Downing, T.E., 1999. Seasonal forecasting of African rainfall: prediction, responses and household food security. Geogr. J. 165, 255. https://doi.org/10.2307/3060442.
Williams, A.P., Funk, C., 2011. A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. Clim. Dyn. 37, 2417–2435. https://doi.org/10.1007/s00382-010-0984-y.
World Bank, 2015. Creating an atmosphere of cooperation in sub-Saharan Africa by strengthening weather, climate and hydrological services. Washington D.C.
World Meteorological Organization, 2011. Climate Knowledge for Action: A Global Framework for Climate Services–Empowering the Most Vulnerable, The Report of the High-level Taskforce for the Global Framework for Climate Services. World Meterological Organization, Geneva.
Yuan, X., Wood, E.F., Chaney, N.W., Sheffield, J., Kam, J., Liang, M., Guan, K., 2013. Probabilistic seasonal forecasting of African drought by dynamical models. J. Hydrometeorol. https://doi.org/10.1175/jhm-d-13-054.1.
Ziervogel, G., Bithell, M., Washington, R., Downing, T., 2005. Agent-based social simulation: a method for assessing the impact of seasonal climate forecast applications among smallholder farmers. Agric. Syst. 83, 1–26. https://doi.org/10.1016/j.agsy.2004.02.009.
Ziervogel, G., Downing, T.E., 2004. Stakeholder networks: improving seasonal climate forecasts. Clim. Change 73–101.
Zucker, G.H., 2017. The variable nature of news media influence. Ann. Int. Commun. Assoc. 2, 225–240. https://doi.org/10.1080/23808985.1978.11923728.