Cognitive Biases about Climate Variability in Smallholder Farming Systems in Zambia

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ABSTRACT

Given the varying manifestations of climate change over time and the influence of climate perceptions on adaptation, it is important to understand whether farmer perceptions match patterns of environmental change from observational data. We use a combination of social and environmental data to understand farmer perceptions related to rainy season onset. Household surveys were conducted with 1171 farmers across Zambia at the end of the 2015/16 growing season eliciting their perceptions of historic changes in rainy season onset and their heuristics about when rain onset occurs. We compare farmers' perceptions with satellite-gauge-derived rainfall data from the Climate Hazards Group Infrared Precipitation with Station dataset and hyper-resolution soil moisture estimates from the HydroBlocks land surface model. We find evidence of a cognitive bias, where farmers perceive the rains to be arriving later, although the physical data do not wholly support this. We also find that farmers' heuristics about rainy season onset influence maize planting dates, a key determinant of maize yield and food security in sub-Saharan Africa. Our findings suggest that policy makers should focus more on current climate variability than future climate change.

1. Introduction

There is mounting evidence of climatic changes in sub-Saharan Africa (SSA), including changes in average and extreme temperatures, changes in rainfall amounts and spatiotemporal patterns, and changes in the frequency and intensity of extreme weather events [see Kotir (2011) for a review]. In addition to the extreme variation in rainfall from year to year, common in semiarid areas, there has been a widespread trend toward more arid conditions and a downward trend in rainfall at the seasonal scale (Nicholson et al. 2018). Although there is substantial uncertainty as to the impacts of climate change on regional rainfall, the two most recent generations of global climate models project reduced spring rainfall over southern Africa by 2100 under a business-as-usual emissions scenario (Lazenby et al. 2018). This result, along with widespread increases in dry spell length, was more recently found by a regional climate model ensemble that simulated the impacts of 1.5° and 2° of warming over southern Africa (Maúre et al. 2018).

These climatic changes contribute to the riskiness of farming and pose a threat to food security in developing countries (Campbell et al. 2016; IPCC 2014; Schmidhuber and Tubiello 2007), particularly for agrarian households who rely on rainfall for agriculture (Jarvis et al. 2011). The impacts of these changes on agriculture are expected to fall most heavily on staple crops, such as maize, grown in SSA's marginal climatic regions (Lobell et al. 2011; Rippke et al. 2016). Climate changes are expected to reduce maize yields by 15% and increase total crop loss by 3% in Zambia by 2055 (Jones and Thornton 2003). In the hottest sites, 1° of warming is expected to lead to maize yield losses exceeding 40% (Lobell et al. 2011).

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While smallholder farmers are particularly vulnerable to climate change, there has been relatively little empirical research about how they perceive climate change or how their perceptions of climate change match observational records and influence their agricultural decisions. A growing body of literature documents smallholder awareness of climate change (Grothmann and Patt 2005; Mertz et al. 2009; Nyanga et al. 2011). There are also studies documenting the prevalence of smallholder ex ante agricultural strategies to adapt to climatic change such as water harvesting or changing to drought-resistant crops (e.g., Eakin 2005; Smit and Skinner 2002; Thomas et al. 2007; Mertz et al. 2009; Jarvis et al. 2011; Mercer et al. 2012). A small but growing number of studies suggest that smallholder perceptions of climate change are not consistent with climate data (Sutcliffe et al. 2016; Simelton et al. 2013; Rao et al. 2011; Osbahr et al. 2011), highlighting the assertion that farmers' behavior can be shaped more by their perceptions of climate change than by the actual patterns of change (Adger et al. 2009). Scholarship to date has relied on meteorological station data to measure patterns of change, which has limited spatial applicability, whereas we compare farmers' perceptions of climate variability with satellite-derived observational data at a national level.

Given the multidimensional nature of the concept of climate, it is not easy to accurately identify changes without extensive recording and processing of hydroclimate data. Even with processing capability, interpretation is often debated and can differ based on factors such as political ideology (Weber 2010; Weber and Stern 2011). The same information can lead two people to opposite conclusions about climate change based on how they personally experience climate impacts (Howe et al. 2015) or how they are economically impacted by climate change (Hsiang et al. 2017). For example, people's attitudes about climate change are affected by whether they locally experience unseasonably warm (or cold) temperatures as opposed to milder temperatures (Bohr 2017). There is evidence of intergenerational changes in the perception of the state of the environment, suggesting that climate change perceptions can vary based on formative experiences (Sáenz-Arroyo et al. 2005). This literature highlights the importance of understanding how individuals interpret climate events or patterns when trying to understand the relationship of climate perceptions with physical data.

Research has shown that people's perceptions and synthesis of climate information can be influenced by psychological biases. A major development in the area of understanding biases in decision-making was the discovery of decision heuristics, or cognitive shortcuts that people use to make decisions, often in situations of uncertainty (Kahneman et al. 1982). One such example is the "availability heuristic," a psychological mechanism where people evaluate the probability of events by the ease with which they come to mind (Tversky and Kahneman 1973). People judge more recent or extreme environmental shocks and disturbances as having a higher probability of occurrence (Morton 2007; Marx et al. 2007; Hertwig and Todd 2005). Perceptions of climate change, therefore, may more accurately reflect perceptions of recent weather events as opposed to long-term climate trends (Zaval et al. 2014; NRC 1999). Another heuristic example is that people tend to underestimate large probabilities (Kahneman and Tversky 1979) and thus underestimate their personal exposure to risk from natural hazards such as extreme weather events (Freeman and Kunreuther 2002). There has been little research addressing climate-related perceptions and, in particular, instances where smallholder farmers may exhibit cognitive bias related to narratives about climate trends. We address a key gap in the literature by matching rich empirical survey data on climate perceptions from small-scale farmers with robust rainfall estimates, typically used to assess regional patterns of climate conditions. We further match perceptions with soil moisture estimates, which are rarely, if ever, considered despite their greater importance for agriculture.

In this paper, we explore farmers' perceptions about rainy season onset related to the fundamental agricultural decision of when to plant the staple maize crop. There is a dearth of meteorological stations across SSA and a lack of capacity in providing or receiving weather information (Parker et al. 2011; Washington et al. 2006), so farmers receive little geospatially relevant weather information to aid decision-making. Hydroclimatological definitions of rainy season onset often use a combination of several empirical rainfall thresholds, involving consecutive days with minimum rainfall amounts without a dry spell in the following days (Boyard-Micheau et al. 2013). However, these definitions do not reflect how farmers individually define rainy season onset and thus are of limited help in understanding actual farm behavior. Our paper demonstrates that rainy season onset is both a hydrometeorological and a social concept. The best time to plant maize in a rain-fed system is highly uncertain. Planting maize too early, prior to consistent rainy season onset, can stunt crop growth or lead to total crop failure, and the farmer will incur the cost to replant. If farmers plant maize too late, they do not maximize the full length of the growing season and thus fail to achieve potential yield.

Farmers in sub-Saharan Africa face a fundamental challenge in choosing the right seed and the right planting date. Hybrid varieties have different maturity periods designed to fit with varying lengths of growing seasons, and in many African countries, earlier-maturing hybrid maize is heavily promoted through government policies (Smale and Jayne 2003). Many parts of SSA are characterized by a distinct wet and dry season, so most farmers only have one chance per year to plant maize, and thus the combination of seed choice and timing of planting is crucial. Farmers are faced with a tradeoff between minimizing weather-related risk by planting a variety that will mature quickly and maximizing yield by planting a later-maturing variety that will produce more grain during the longer maturation period. Selecting a seed variety that will perform well in a given agroecological environment and choosing the optimal sowing date is cognitively challenging and can have very large differences in yield outcomes for farmers (Akinnuoye-Adelabu and Modi 2017).

Agricultural subsidy programs, providing fertilizer and often hybrid seed, are ubiquitous and politically popular in Africa, including in Ethiopia, Ghana, Malawi, Nigeria, Tanzania, and Zambia (Mason and Ricker-Gilbert 2013). In Zambia, new hybrid maize varieties combined with subsidized credit for seed and fertilizer led to a doubling of maize area during the 1970s and 1980s (Smale et al. 2015) and near-universal adoption in Zambia (Smale and Jayne 2003). Hybrid maize varieties in Zambia are bred for a single predominant characteristic: to mature earlier in the season. These hybrids are characterized as very-early-, early-, and medium-maturing varieties, and their potential yield and price are inversely correlated with their length of maturity. The current version of the support program is the Farmer Input Support Program (FISP), which originally distributed a single medium-maturing hybrid maize variety to all eligible farmers. In the last decade, the program has gradually allowed farmers greater choices of seeds, although poor information exchange about varieties from seed companies and agricultural extension has resulted in ''choice overload'' for farmers (Waldman et al. 2017).

We examine farmers' perceptions of rainy season onset, using their heuristics, and compare these with satellite-derived rainfall data and high-resolution soil moisture estimates. We elicited heuristics farmers use to determine both (i) rain onset and (ii) appropriate planting time through household surveys across Zambia. Farmers were asked to recall rain onset in the previous four seasons and approximately a decade ago [see the methods section (section 2) for more detail]. Rainfall data are at 5-km daily resolution from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) dataset (Funk et al. 2015). Soil moisture estimates are at a 1-km daily resolution estimated using HydroBlocks, a hyper-resolution, physically based land surface model (Chaney et al. 2016). We translated farmer heuristics into biophysical metrics that best represent those heuristics. For farmers who expressed heuristics based on rainfall duration or frequency, we used CHIRPS, and for heuristics related to soil moisture amount, we used the HydroBlocks model to determine a rain onset date. We then compared the physically derived rain onset date with farmer-recalled rain onset and their actual planting dates during the 2015/16 season.

The following research questions guide our analysis:

1) Are smallholder farmers' perceptions of climate variability consistent with observational records?
2) Is there evidence that farmer perceptions are cognitively biased, and if so, what is the source of this bias?
3) Are heuristics about rainy season onset and planting time associated with agricultural decisions, and if so, does this alter how farmers can adapt to climate variability?

We choose to frame the problem as a ''cognitive bias'' in the sense that we investigate whether there is a perceptual distortion related to narratives about climate change. We acknowledge that climate data are not necessarily the ''truth,'' and farmers' perceptions are not necessarily right or wrong, but rather focus on whether there is a systematic pattern to farmers' perceptions of rainy season onset.

These research questions are explored in Zambia, a country in SSA that chronically struggles with food insecurity and where drought events frequently result in local- or even regional-scale crop failure. Our study focuses on smallholder farmers in a region characterized by strong rainfall seasonality and substantial rainfall variability (see Figs. 3, 4, and 10). Zambia is typical of savanna range countries, which are expected to be the global center of agricultural development in SSA in the next few decades (Estes et al. 2016).

2. Methods

a. *Rainfall and maize production in Zambia*

The majority of farming in Zambia is rain-fed agricultural production with little possibility of irrigation. The rainy season is unimodal and runs from October or November until March or April. Mean annual rainfall ranges from 500 to 1400 mm annually, depending on the location within Zambia. The map below (Fig. 1) illustrates mean annual rainfall in Zambia from the period 2000–16, showing annual rainfall as low as 500 mm in the south and as high as 1400 mm in the north and northwest of the country. Figures 2 and 3 illustrate the

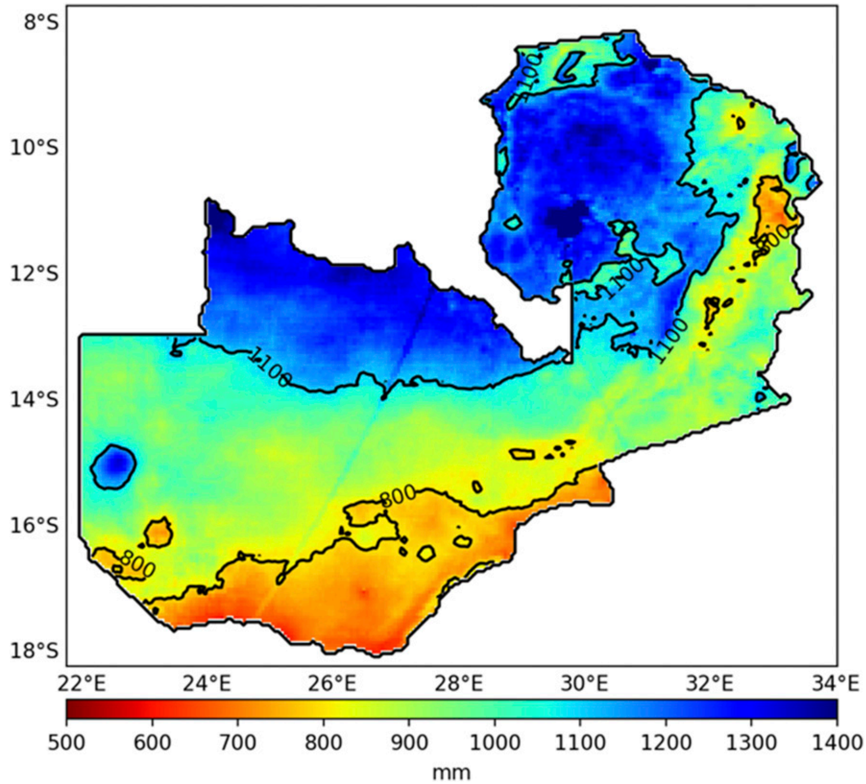

FIG. 1. Mean annual rainfall map of Zambia, 2000–16. Author derived estimate using CHIRPS (Funk et al. 2015) and displays three zones over the 2000–16 period constructed by tracing natural breaks in the climatological data. These rainfall zones range from dry (zone 1: <800 mm annually) to intermediate (zone 2: 800–1000 mm annually) to wet (zone 3: >1000 mm annually).

coefficient of variation of rainfall and the mean soil moisture estimates over the same period.

There is a significant difference in rainfall patterns within the country, defined by distinct precipitation zones. Figure 1 displays three zones over the 2000–16 period constructed by tracing natural breaks in the climatological data. The zones range from dry (zone 1: <800 mm annually) to intermediate (zone 2: 800–1000 mm annually) to wet (zone 3: >1000 mm annually) and are used in the proceeding analysis to disaggregate the data for clearer comparison. These different precipitation zones define the potential growing season length. The respective season length in dry, intermediate, and wet zones is <120, 120–150, and 150–190 days, respectively. These growing season lengths roughly accommodate early-, medium-, and late-maturing hybrid maize varieties, respectively. In addition to significant variation in mean annual rainfall, there is significant intra-annual variation in rainfall. While 500 mm yr^{-1} can be a sufficient amount of rainfall for crop production, high variation in the form of long dry periods or intense weather events could translate into a poor growing season or total crop loss. In other words, interannual variability could be the difference between a very good year and a famine.

Smallholder farmers comprise more than 95% of farmers in the country of Zambia, cultivating fewer than 5 hectares of land, although the number of medium-size farmers (cultivating between 5 and 20 hectares of land) is increasing (Sitko and Jayne 2014). Maize is the dominant staple crop in Zambia, grown by 82% of farming households and accounting for approximately 57% of total caloric consumption (Sitko et al. 2011). Average maize yields are approximately 2.2 t per hectare (1 t = ~907 kg) in Zambia, approximately 20% of the average yield in the United States (Purdy and Langemeier 2018).

b. *Household perceptions of rainfall*

Household-level surveys were conducted with 1171 farmers in June and July 2016, following the crop harvest. Survey questions focused on basic demographics; socioeconomic indicators; production data from the 2015/16 season; and perceptions about rainfall onset, drought probabilities, and precipitation uncertainty. We sampled households in two districts in each of six provinces as follows: Central (Mkushi, Mumbwa), Copperbelt

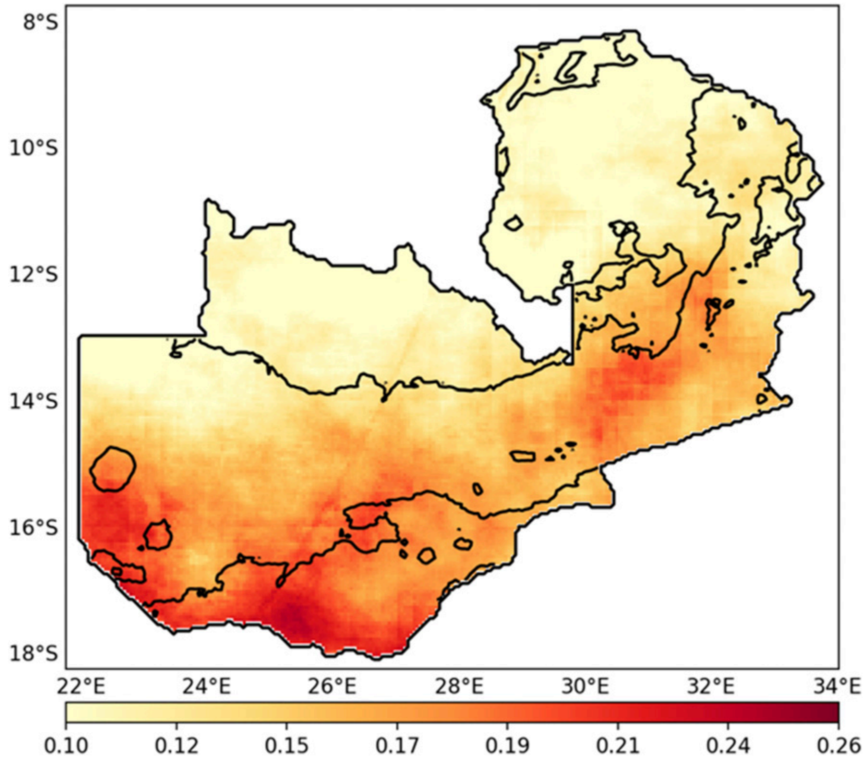

FIG. 2. Coefficient of variation of annual rainfall, 2000–16. Scale is the coefficient of variation (standard deviation/mean) in annual rainfall.

(Mpongwe, Masaiti), Eastern (Lundazi, Petauke), Northern (Mbala, Mungwi), Northwestern (Mufumbwe, Solwezi), and Southern (Choma, Namwala). These districts span all three precipitation zones.

Our sampling methodology involved identifying primary, secondary, and tertiary markets from the district town in two directions and sampling households around the tertiary markets. Primary markets are largely aggregating markets in the district town, secondary markets are markets along main paved roads where vendors travel to sell goods to people from other areas within the district or camp, and tertiary markets are an assemblage of vendor stands in rural areas accessed on foot by the local community. Once we identified a tertiary market, we sampled 30 households by walking along dirt paths or roads from those markets in each direction and randomly selecting households along the paths. The spatial structure of the road network and household settlement patterns varied across market locations. In general, households were located within an 8 km × 8 km area in each sampled market area. We followed the same protocol but with a denser sampling of market nodes and households in Southern Province because of the smaller area that falls within this precipitation zone. We chose this sampling strategy as a way to ensure that we were consistently selecting rural households in each district.

The central survey questions we used to characterize farmer perceptions of climate variability included farmer recollection of when the rains arrived in previous seasons and heuristics the farmer uses to determine (i) rainy season onset and (ii) when to plant maize. We asked farmers to recall when the rainy season arrived in each of the last four growing seasons and about 10 years ago. Based on informal interviews with farmers, we were not confident farmers could reliably recall specific planting dates prior to four growing seasons ago. Thus, when asking about rainy season onset from 10 years ago, we emphasized that we were not asking about a specific year and rather asked the farmer to think generally about the rains "around 10 years ago." Farmers generally were able to recall planting dates with a precision of a 1-week window, so predefined responses were based on weekly intervals (first week of October, second week of November, etc.). We also asked farmers a series of structured questions related to heuristics about rainy season onset. Response categories were developed through informal interviews and field testing prior to development of the structured surveys. We provided respondents with four categories that consistently emerged from the field testing and an open-ended category to capture other responses. Farmers were asked to only offer a single response.

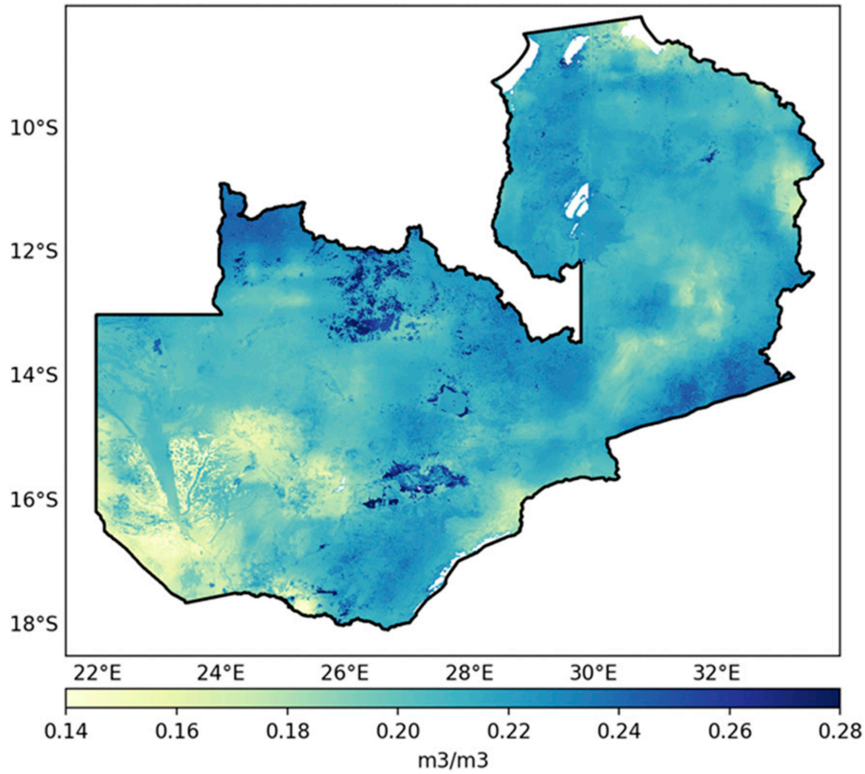

FIG. 3. Mean annual soil moisture, 2000–16. Soil moisture at 1-km resolution derived from the HydroBlocks model in units of volume of water/volume of soil.

In addition to these questions, we also asked farmers about their perceptions of the likelihood of drought occurring and their general perceptions of risk associated with drought and dry spells. The date, variety, and quantity of each time a farmer planted maize were also recorded. In the analysis, we included various socioeconomic variables related to asset ownership. We created an *asset index* based on the first principal component of a list of common household assets owned by each household and divided it into quintiles. This approach is similar to common approaches of estimating asset ownership in areas where formal income is not common (Filmer and Pritchett 2001). We created a livestock index by converting livestock to tropical livestock units (TLU). We used a weighting formula to calculate TLU, according to index guidelines developed at the Food and Agriculture Organization (Jahnke et al. 1988).

c. Matching farmer perceptions and observational data

Physical estimates use the best currently available high-resolution gridded rainfall and soil moisture hydrometeorological products. We use satellite-derived rainfall from the CHIRPS dataset (Funk et al. 2015). This dataset was selected given its quasi-global coverage from 1981 to present with 5-km daily resolution. CHIRPS combines satellite imagery and station data to create a bias-corrected gridded rainfall time series for trend analysis. The technique was developed to produce precipitation maps for drought detection and environmental monitoring in areas where there is a dearth of surface data. Although rainfall station data are sparse in developing countries, the CHIRPS dataset performs better than coarser satellite-derived and gauge-corrected rainfall products (Beck et al. 2017). The high spatial resolution of CHIRPS captures rainfall spatial variability and land heterogeneity (Musau et al. 2016), which are important in this context given the ubiquity of convective rainfall in this region and the finescale of household-level perceptions.

The high-resolution 1-km daily soil moisture estimates were derived with one of the latest-generation land surface models: HydroBlocks. HydroBlocks is a physically based hyper-resolution land surface model based on the Noah-MP (Ek et al. 2003) vertical land surface scheme applied to the concept of hydrologic response units (HRUs). The HRUs represent areas of similar hydrological behavior that are derived by clustering high-resolution proxies of the drivers of spatial heterogeneity including soil properties, topography, and land cover. At each time step, the land surface scheme updates each HRU, and the HRUs dynamically interact laterally via subsurface and surface flow. HydroBlocks outperforms both satellite-derived soil moisture and large-scale land surface models when compared to in situ ground measurements (Pan et al. 2016; Cai et al. 2017).

The hydrological processes were simulated at 3-hourly, 30-m resolution between 1980 and 2016. We used 3-hourly, 5-km meteorological data (Princeton Global Forcing; Sheffield et al. 2006); 30-m topography (SRTM; Farr et al. 2007); 30-m Landsat-derived land-cover type (GlobeLand; Chen et al. 2014); 250-m soil properties (SoilGrids; Hengl et al. 2017); 30-m Landsat-derived NDVI (USGS; Roy et al. 2010); and 30-m Landsat-derived fraction of water, bare soil, and tree cover (USGS; Hansen et al. 2013). The simulation ran for 120 h with 500 cores on the Princeton University High-Performance Supercomputing facility. The soil moisture output was upscaled to 1-km daily resolution to reduce data volume.

We obtained the coordinates of each interviewed household following the household survey using a GPS device. The household location was then overlaid on the 5-km-resolution gridded rainfall data and 1-km-resolution soil moisture data, allowing us to obtain a precipitation and soil moisture history for each household. To harmonize the social and environmental data, we translated farmer heuristics into hydrometeorological physically based metrics to define the rain onset and planting dates. This allowed us to interpret rainy season onset using physical data in the same way that a farmer perceives the onset of the rainy season. Thus, we used the farmers' reported heuristics as a guideline to define these metrics, as well as to capture the uncertainties in the environmentally based metrics. When farmers were asked about how they decided when it was the start of the rainy season, their answers ranged from *after the first day of heavy rainfall*, *after a few consecutive days of rain*, or *when there is enough soil moisture* to various other *natural signs* related to cloud density and movement or ecological indicators. We created rainfall- and soil-moisture-based metrics for each of the three major reported heuristics (details below). We did not create a metric for the *natural signs*, given the lack of rainfall-based translations.

To evaluate the degree to which farmers' perceptions were consistent with the physical data of rainy season onset, we compare farmers' perceptions with the physically estimated rainy season onset adjusted by farmers' heuristics. Using farmers' own cognitive rules for determining rainy season onset gives us a more nuanced way to capture the subjectivity of the onset of the rainy season. This approach allows us to control for error related to the subjectivity of onset perception and highlights the heterogeneity in these perceptions. Our analytical approach is novel in that it goes beyond much simpler approaches comparing perceptions with single meteorological station records to attain a much finer-scale measure of rainy season onset. In addition, rather than simply using a standard metric for rainy season onset, we use an approach that accounts for differences in how people cognitively process rainy season onset.

TABLE 1. Farmers' heuristics on the start of the rainy season and rainfall-derived metrics.

Farmers' heuristics	Rainfall-based metric with confidence bounds
First day of heavy rain	First day > 10 ± 5 mm
Few consecutive days of rain	3 consecutive days >1 mm rain ± 1 day
Soil moisture	(0.70 ± 0.25) × TAW

The *first day of heavy rain* heuristic was translated into a rainfall-based metric in which rainy season onset was defined as the first day in which at least 10 mm of rain fell following the end of the dry season. To account for uncertainties in this metric, we also tested alternative versions using daily rainfall thresholds of 5 and 15 mm and include this range of uncertainty in the visual display of data. Excluding amounts of precipitation less than 5 mm omits what farmers often refer to as "false rains," which are brief precipitation events that are not consequential for crop production.

The *few consecutive days of rain* heuristic was translated to a metric wherein the rain onset was defined as the last of at least 3 consecutive days during which rainfall was greater than 1 mm on each day. Since "a few days" of rain is a vague definition, we include an uncertainty range for this metric varying between 2 and 4 days. This metric focuses on rainfall duration.

The *soil moisture* heuristic for the start of the rainy season was implemented based on the total available water (TAW; Allen et al. 1998). A certain threshold of TAW is the soil moisture level at which plants can easily extract water from the soil, with unrestricted growth, being neither waterlogged nor water stressed. We assume this TAW threshold to be the soil moisture held between field capacity and wilting point and use the date at which 70% TAW is first reached as the soil moisture heuristic, with 25% uncertainty bounds above and below.

Table 1 summarizes the translation of the rainy season onset heuristics into physically based rainfall and soil moisture metrics. Once the physically based metrics were defined, we computed these for each household

TABLE 2. Date farmers perceived rainy season onset (all observations).

Year	Mean date[a]	Std dev	Obs (n)	Response rate
2015	324.3	16.9	1172	100%
2014	319.6	15.3	1131	97%
2013	315.5	12.7	1037	88%
2012	311.7	12.3	1016	87%
~2005	302.5	10.1	1146	98%

[a] For comparison, farmer perceptions were converted from weeks to the central date of the week expressed in Julian calendar days.

location based on the heuristic they specified. We then compared the density distribution of the physically defined rainy season onset with the farmer's stated perception of rainy season onset for the following growing seasons: 2015, 2014, 2013, 2012, and about 10 years ago (which is an average of the 2004–06 seasons). Because of limitations in farmer recall, the perceptions were reported based on the week of the year (first week of October, second week of November, etc.), so for practicality, we used the central day of the given week, which presents some inconsistency in the alignment of the social and environmental data.

3. Results and discussion

a. *Farmer perceptions of rainfall*

Farmers perceive that rains began earlier the farther back in time they were asked to recall rainfall onset dates (see Table 2). See Fig. 4 for a crop calendar displaying the range of planting months and variability in growing season length. On average, farmers perceived that the rainy season onset during the 2015/16 growing season (2015 from here on) was 21.8 days later than it was 10 years ago and approximately 12.6 days later than it was during the 2012/13 season. The standard deviation in their responses also decreased with recall, with the highest standard deviation occurring in the previous season and the lowest occurring approximately 10 years ago. This suggests that the heterogeneity in farmer responses is trending toward a mean as a result of cognitive bias. Additionally, the number of people who were unable to recall rainy season onset increased with recall each year, except for ''about a decade ago'' (~2005), when 98% of respondents provided a rainy season onset date. While farmers admittedly have difficulty recalling rainy season onset two to four seasons ago, they nearly all have a perception about a longer time horizon.

The different hydroclimate patterns across Zambia create wide variation in rainy season onset among and within the three rainfall zones. Despite these climatic differences, trends in farmers' perceptions are clear across Zambia. To look more closely by precipitation zone, we subdivided the data and plotted distributions of the perceived rainy season onset. Figure 5 depicts the distribution of farmers' rain onset estimates by week for each rainfall zone from dry (Fig. 2a) to intermediate (Fig. 2b) to wet (Fig. 2c). Despite the differences in rainfall seasonality among the zones, the same pattern of farmers' perceptions seen in Table 3 holds across all three zones but is clearest in the driest zone (zone 1; Fig. 5a). The more recent seasons have wider variation in responses, with the 2015/16 season demonstrating the widest variation and also the latest average onset. The 2014/15 season showed less spread and earlier peaks. The relationship persists throughout the data to 10 years ago, when farmers recall the rainy season onset to have taken place during the last week of October. These data depict a clear perception among farmers that rainy season onset is getting later.

Figure 6 summarizes the difference between farmers' perceptions of rainy season onset in the previous season (2015/16) and about 10 years ago (~2005). The vast majority of farmers (88%) perceive the rain onset to be getting later over the last 10 years, indicated by a positive difference between 2015/16 and ~2005. Fewer than 5% of farmers perceived the rains to be getting earlier (negative value), and approximately 7% perceived no difference in rain onset. On average, farmers perceive the rains to be arriving 21.9 days (or about 3 weeks) later over the 10-yr period.

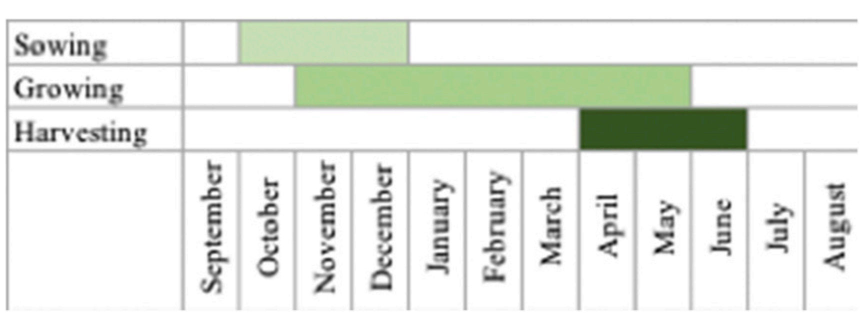

FIG. 4. Maize production calendar for Zambia.

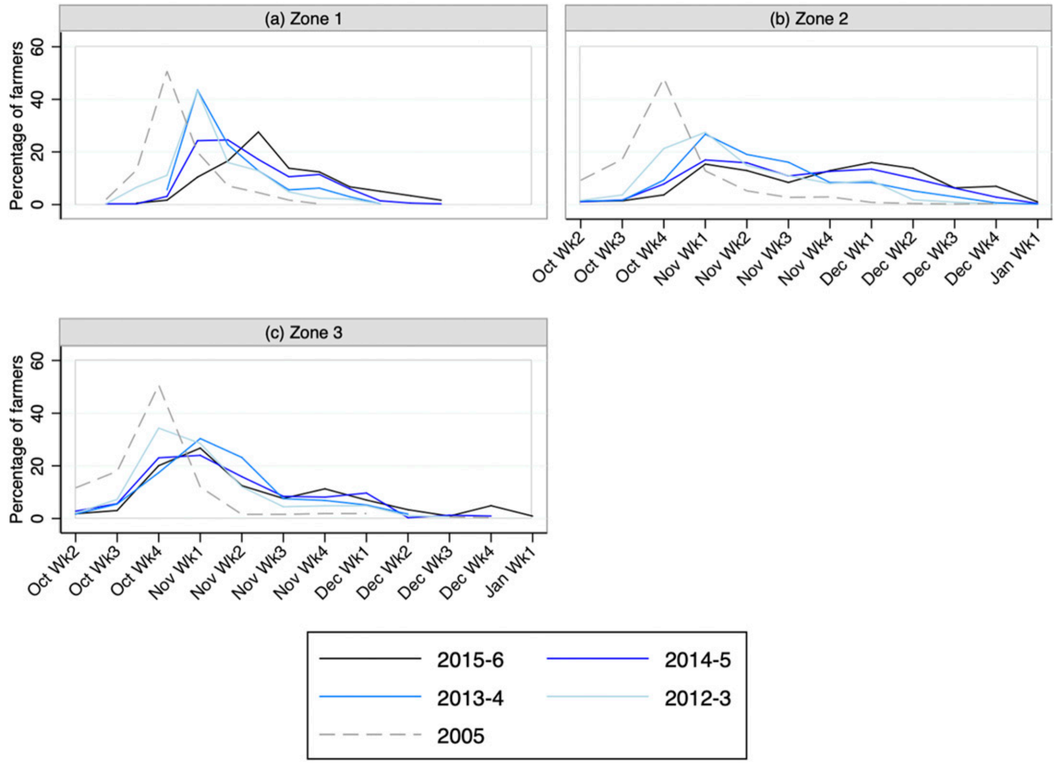

FIG. 5. Percentage of farmers indicating different rainy season onset dates for ~2005, 2012, 2013, 2014, and 2015.

b. Perceptions and cognitive biases

To understand factors associated with the perceived change in rainy season onset, we estimated a fixed effects regression model, where the dependent variable is the difference between an individual farmer's perceptions of the change in rain onset from 10 years ago and from the 2015/16 season (see Table 4 for summary statistics of households). The fixed parameter included is the district to roughly capture location-specific effects such as the clustering of observations resulting from similar rainfall patterns across space. As independent variables, we included basic sociodemographic variables such as age, gender, the number of maize fields planted, a basic asset index, a livestock index, the amount of income they derive off farm, and the

TABLE 3. Variables associated with the perception of later rainy season onset. Note that *** indicates statistical significance at the 1% level; ** indicates statistical significance at the 5% level. SE is standard error.

Variable	Coeff	SE	$P > t$
Gender of household head (male = 1)	3.644	1.410	0.01
Education of household head (years)	−0.897	0.400	0.03
Number of plantings	−0.411	0.620	0.51
Asset index (1–5)	−0.382	0.465	0.41
Livestock (TLU)	0.039	0.035	0.25
Off farm income (Kwacha)	−0.006	0.005	0.24
Maize in storage (kg)	−0.032	0.020	0.10
Longest dry spell length (days)	0.157	0.062	0.01
Perceived frequency of drought (years)	−0.200	0.146	0.17
Constant	21.977	2.347	0.00
Observations	1105		
Groups (fixed effect = district)	12		
R2 (within)	0.03		
R2 (between)	0.45		

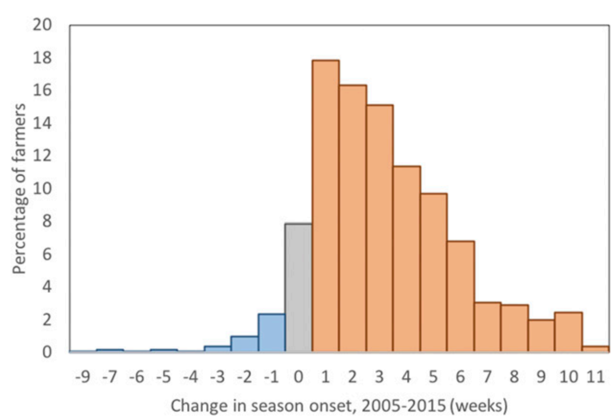

FIG. 6. Farmers' perceived changes in the rainy season onset over the last 10 years. Values to the right of zero indicate a positive change in the onset week (rains later), while values to the left indicate a negative change (rains earlier).

TABLE 4. Descriptive statistics of farmers/households sampled. Asset index ranges from 1 (lowest) to 5 (highest). Educational attainment categories are as follows: none (1), some primary (2), completed primary (3), some secondary (4), completed secondary (5), some postsecondary (6), and completed postsecondary (7).

Variable	Mean	Std dev	Min	Max
Gender of household head (male = 1)	0.8	0.4	0	1
Education of household head (1–7 categories)	3.2	1.6	0	7
Number of plantings	1.7	1.0	0	5
Asset index (1–5 categories)	3.0	1.4	1	5
Livestock (TLU)	3.4	22.8	0	722
Off farm income (in hundreds of Kwacha)	72.7	138.6	0	1800
Maize in storage (in hundreds of kg)	17.4	40.7	0	1000
Longest dry spell length (days)	21.0	10.0	0	60
Perceived frequency of drought (years)	5.5	3.9	1	10

amount of maize they have in storage. We also included a set of independent variables to capture psychological factors that might impact a farmer's cognitive bias related to rainy season onset. These include the length of the longest dry spell they experienced during the growing season and their perceptions of the frequency of drought.

Our findings support the notion that climate perceptions and biases may be related to sociodemographic factors, such as gender and education, as wel as psychological factors related to food insecurity and rainfall events (see Table 3). On average, men perceive the rains to start 3.5 days later over a 10-yr period than women. One additional year of education reduces the perception of the rainy season onset arriving later by almost a week. Another significant variable that is associated with the perception that the rains are getting later is the length of the longest dry spell in the previous season. For each additional day of dry spell, farmers perceive the rains to be 0.15 days later.

Figure 7 displays the distribution of heuristics farmers use to characterize rainy season onset. The most prevalent response from 36% of respondents is that they perceive the rainy season to start after the *first day* of heavy rainfall. Slightly fewer respondents (31%) reported that they perceive the rainy season to start after a few *consecutive days* of rainfall. Approximately 17% of respondents reported using a heuristic that could be categorized as *other*, mostly involving movement, size, and density of storm clouds but also ecological indicators such as the presence of certain butterfly species. About 15% of respondents perceive the rainy season to start when there is sufficient *soil moisture*. Only about 2% of respondents define the rainy season by the *cumulative amount* of rain.

c. Comparing perceptions and physical estimates of rainfall onset

Figure 8 displays a series of individual figures comparing the density of farmer-perceived and biophysical rainy season onset for each zone in each year. The areas under the curves represent the density of farmer ''perceptions'' of rainy season onset and the ''physical metric'' defining rainy season onset across the initial weeks of the growing season. Biophysical metrics of rain onset are defined by using farmer heuristics to determine the biophysical threshold of rain onset. For example, if a farmer reported that they perceive rain onset to start after the first day of heavy rain, we compared their perceived date of rain onset with rain onset as defined by the first day of heavy rain recorded in the CHIRPS data for that household location. The shaded area around the physical metric represents the uncertainty involved in converting heuristics into physical metrics.

Figure 8 shows that on average, the accuracy of farmers' perceptions gets worse when they are asked to recall more distant seasons. Farmers' perceptions of onset and the physically derived onset have similar distributions in the most recent season (2015), where the mean perceived rain onset is almost identical to the mean physically derived onset. The physically derived data are less smooth than the perception data and often have multiple peaks, reflecting the heterogeneity in rainy season onset across the country. The smoothness

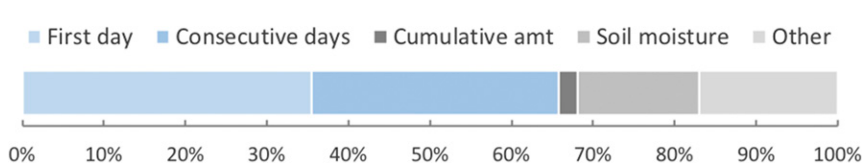

FIG. 7. Heuristic determining perceived rainy season onset (% of farmers using each heuristic).

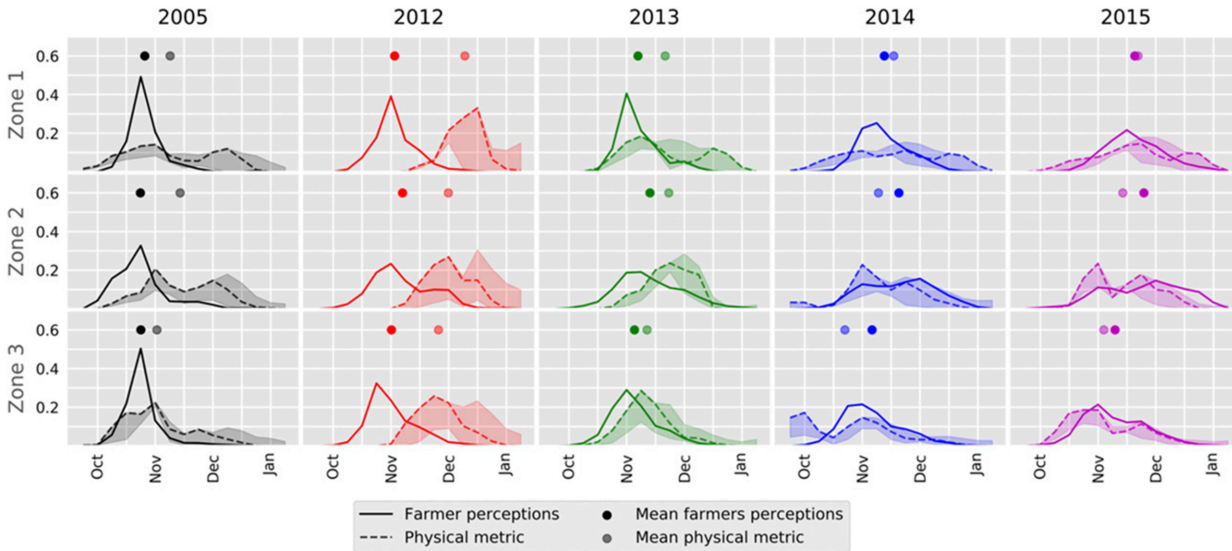

FIG. 8. Farmer perceptions vs physically derived rain onset (physical metric) by year and precipitation zone. Perceived and physical metrics are different in all but zone 1, 2015. The figures for 2005 are an average for the seasons beginning in 2004, 2005, and 2006. Shaded area represents the uncertainty parameters described in Table 1.

of the perceptions is likely attributable to recall bias. Starting in 2013, the mean of the perceptions and the physical data diverges as farmers recall earlier rainy season onset for previous seasons. In 2012, there is the largest discrepancy between perceived and actual observations, with average farmers' perceptions of rainy season onset occurring almost 5 weeks earlier than the average physically derived onset. This suggests that their perceptions of the typical interannual variability of rainfall are overridden by a narrative among farmers that the rains are arriving later. This narrative has been documented by Mulenga et al. (2017). The data provide evidence of recall bias that sets in as early as 1 year after harvesting and a systematic deviation resulting from the widely held perception that the rainy season starts later each year. Statistical tests of the differences between perceived and observed rainy season onsets can be found in Table 5.

In addition to a perceptual distortion about rainy season onset getting later, there is also evidence of cognitive bias related to anchoring in the more distant past. Farmers' perceptions of rainy season onset "about a decade ago" appear to reach a ceiling, with a narrower range of responses with a median around the fourth week of October. There is a common narrative among farmers in Zambia that the rainy season is getting later and previously started in October, and we see that farmers' perceptions form a relatively normal distribution with a steep peak anchored around the last week of October. In other words, their perceptions of rainy season onset in the distant past (more than a few years ago) appear to be anchored around this narrative and date. While using approximately 10 years ago does not capture perceptions of the multidecadal nature of climate perceptions, it does start to uncover farmer cognition about weather beyond simply interannual variability. While there are some limitations to asking farmers in this way, we felt it was better than directly asking about a trend, which would likely prime them to recall what they have heard about trends in the climate.

d. *Influence of perceptions on planting behavior*

We included several questions in our survey to better understand how heuristics influence not just perceptions of rainy season onset, but also actual agricultural practices. We asked farmers *what* heuristic they use when they decide when to plant maize (Fig. 9). The most common heuristic, cited by approximately 43% of the sample, is *soil moisture*.

TABLE 5. Paired t test between average perceived and observational rainy season onset dates (in days).

	Zone 1		Zone 2		Zone 3	
	Diff	t	Diff	t	Diff	t
2015	−1.6[a]	−1.1	10.2	7.6	5.4	5.3
2014	−4.5	−3.0	10.0	7.7	13.1	9.7
2013	−13.2	−10.8	−9.1	−9.1	−6.1	−7.3
2012	−34.1	−43.9	−22.3	−22.2	−22.8	−27.6
2005	−7.2	−5.5	−15.0	−13.3	−7.3	−10.0

[a] Not significantly different at any conventional level. All other paired comparisons statistically significant at the 1% level or better.

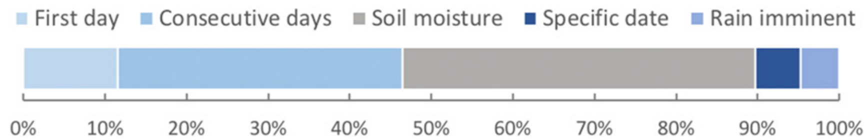

FIG. 9. Heuristic determining when to plant (% of farmers using each heuristic).

The next most common response (35%) was from farmers who reported that they wait for a few days of *consecutive rain* before planting. Approximately 12% of farmers reported that they plant after the *first day* of heavy rain, while fewer than 10% wait for a *specific date* or until the *rain is imminent*.

To evaluate whether farmers' choices of heuristic influence their maize planting dates, we examined how the heuristics are related to when farmers planted their first maize crop in the 2015 season. Planting dates differ across precipitation zones in Zambia, as they are based on the length of the growing season and the total quantity of rainfall. Since farmers can have multiple maize plantings, we focus on the date of each farmer's earliest maize planting. Figure 10 displays the distribution of farmers' earliest maize plantings in each week, disaggregated by precipitation zone. Farmers in zones 1 and 2 planted maize with relatively normal distributions centered on the first week of December. Farmers in the wettest zone were able to plant earliest on average, with a median planting date in the second week of November.

We then group their actual planting dates by heuristic category to look for differences in mean planting date. Heuristics about when it is time to plant maize influence the date farmers actually plant (Fig. 11). Farmers who use heuristics such as *on a specific date* plant the earliest, followed by those who rely on a sense that the *rains are coming* or plant after *a single day of heavy rain*. The latest median planting date is for farmers who wait for several days of consecutive rain or for adequate *soil moisture*. Importantly, the use of heuristics clearly influences not only the perception of rain onset, but also the actual planting date in a given season. Further details about how perceptions of rain onset getting later influence seed choice are presented in a separate publication (Waldman et al. 2017).

4. Conclusions

We find that while the vast majority of farmers perceive the rainy season onset to be getting later, this perception is not wholly consistent with observed physical data. This mismatch is important for multiple reasons. Farmers are unable to accurately recall when the rains started beyond 2–3 years, so it is not surprising that their longer-term recall about weather trends is biased as well. Biases related to rainy season onset influence the decision of what date to plant, which is an important determinant of yield outcomes. While some of this bias can be explained by sociodemographic factors such as gender and education, or psychological factors such as

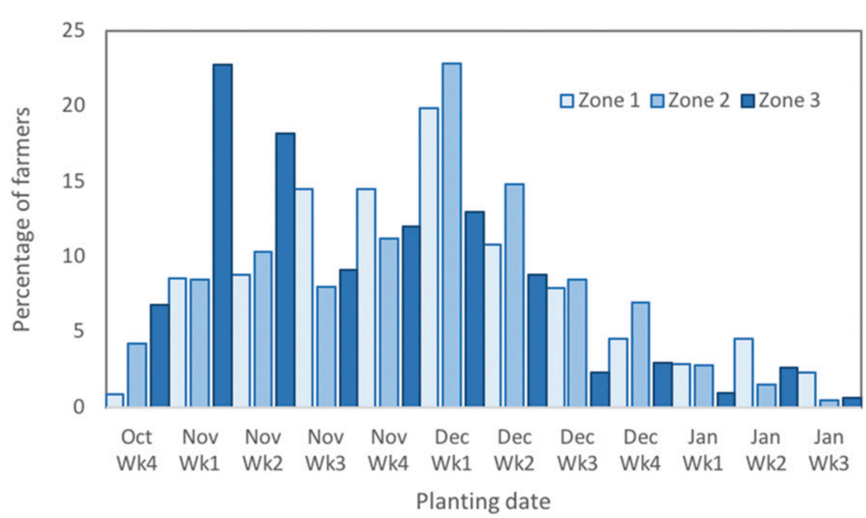

FIG. 10. Actual planting dates by precipitation zones. Zone 1 is dry, zone 2 is intermediate, and zone 3 is wet.

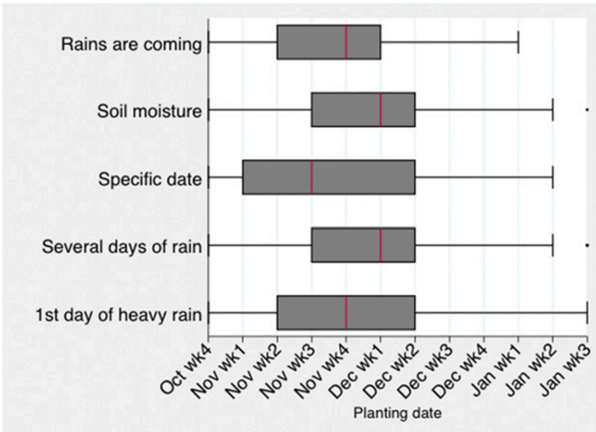

FIG. 11. Boxplots of planting date by rain onset heuristic category. Boxplots represent 25th, 50th (median), and 75th percentiles of observed data.

food inadequacy, much of this bias appears to be related to perceptions of climate trends. We also provide evidence that heuristics about the appropriate time to plant are correlated with actual planting dates, and this reliance on heuristics is presumably related to uncertainty about when to plant. Certain heuristics are associated with earlier planting, while other heuristics are associated with later planting decisions. While cognitive shortcuts can be efficient and alleviate taxing mental calculations (Goldstein and Gigerenzer 2002), they can also be associated with recall bias and lead farmers to suboptimal decision-making. We explore this suboptimality in a separate publication, where we find that perceptions of the rain onset getting later influence seed choice and that in general, seed choice does not correlate well with growing season length (Waldman et al. 2017).

Farmers receive information about the climate through various channels, including through signals sent by agricultural policies. Policies promoting earlier-maturing hybrids likely intensify the perception that the season is getting shorter, thus nudging farmers toward behavior that aligns with this perception. Our findings raise questions about the drawbacks from national policies that fail to consider heterogeneous weather and climate conditions and are more focused on future climate change than current climate variability. Policy and technology that focus on understanding rainfall and climate variability and that involve information exchange with farmers are crucial to addressing current food security needs.

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