Smallholder Knowledge of Local Climate Conditions Predicts Positive On-Farm Outcomes

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(Manuscript received 7 September 2021, in final form 9 March 2022)

ABSTRACT: People's observations of climate change and its impacts, mediated by cultures and capacities, shape adaptive responses. Adaptation is critical in regions of rainfed smallholder agriculture where changing rainfall patterns have disproportionate impacts on livelihoods, yet scientific climate data to inform responses are often sparse. Despite calls for better integration of local knowledge into adaptation frameworks, there is a lack of empirical evidence linking both smallholder climate observations and scientific data to on-farm outcomes. We combine smallholder observations of past seasonal rainfall timing with satellite-based rainfall estimates in Uganda to explore whether farmers' ability to track climate patterns is associated with higher crop yields. We show that high-fidelity tracking, or alignment of farmer recall with recent rainfall patterns, predicts higher yields in the present year, suggesting that farmers may translate their cumulative record of environmental knowledge into productive on-farm decisions, such as crop selection and timing of planting. However, tracking of less-recent rainfall (i.e., 1–2 decades in the past) does not predict higher yields in the present, while climate data indicate significant trends over this period toward warmer and wetter seasons. Our findings demonstrate the value of smallholder knowledge systems in filling information gaps in climate science while suggesting ways to improve adaptive capacity to climate change.

KEYWORDS: Africa; Cloud tracking/cloud motion winds; Precipitation; Climate variability; Satellite observations; Bayesian methods; Seasonal forecasting; Interannual variability; Intraseasonal variability; Adaptation; Agriculture; Climate services; Decision making; Indigenous knowledge

1. Introduction

Climate change impacts are disproportionately experienced in regions of the developing world where rainfed farming systems are predominant (Adger et al. 2003; Kotir 2011). And yet, many such areas of vulnerability are those least understood by climate science, where station-based observations are sparse and long-term records incomplete (Boko et al. 2007; Alexander et al. 2011; Nakashima et al. 2012; Kizza et al. 2009). While recent calls acknowledge the need for better engagement of existing climate data sources with local knowledge systems—to both fill gaps in climate science and support on-farm adaptive capacity—such engagement remains poorly developed (Roncoli 2006; Alexander et al. 2011; Savo et al. 2016).

In this paper, we combine scientific climate data with local knowledge systems from a climatically complex transition zone of equatorial Africa. We explore an outstanding question about smallholder climate observations (Kotir 2011; Waldman et al. 2019a): are farmers who observe rainfall patterns with higher fidelity over time associated with higher yields in the present, suggesting the capacity to adapt farming practices in response to variable and changing climate?

Variable and changing rainfall patterns pose significant challenges in smallholder farming systems (Kotir 2011; Nakashima et al. 2012). Smallholders employ flexible livelihood strategies to adapt to change and minimize risk (Adger et al. 2003), and effective adaptation depends on information drawn from both social and biophysical environments (Roncoli 2006; Crane et al. 2011). For instance, farmers may anticipate changes in timing and duration of seasonal rainfall by observing recent rainfall or other environmental signs (e.g., plant flowering, migratory bird behavior), which inform real-time decisions to alter crop type or timing of on-farm activities (Orlove et al. 2010; Salerno et al. 2019; Kotir 2011). Individual observations are also updated with information accessed through social networks, such as from trusted kin, agricultural extension services, or scientific

Supplemental information related to this paper is available at the Journals Online website: https://doi.org/10.1175/WCAS-D-21-0131.s1.

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DOI: 10.1175/WCAS-D-21-0131.1

forecasts, which may facilitate more effective decision-making, particularly in the context of noisy environmental signals (Crane et al. 2011). However, smallholder knowledge systems are increasingly strained under variable and changing climate, as rainfall patterns begin to depart from the deep temporal record of culturally transmitted past observations (Alexander et al. 2011; Nakashima et al. 2012). If the ability to make real-time adaptive decisions erodes, this may compound climate impacts on yields and system sustainability (Adger et al. 2003; Boko et al. 2007; Simelton et al. 2013).

Understanding the timing and duration of seasonal rainfall in data-deficient regions remains particularly challenging for climate science. In equatorial Africa, much of the region has two rainy seasons associated with the twice-annual passage of the tropical rain belt, with interannual variability arising from teleconnections among remote atmospheric and oceanic phenomena (Nicholson 2017; Diem et al. 2021). The late twentieth–early twenty-first century trends in each season's rainfall differ markedly in various rainfall data products (Maidment et al. 2015). Future trends, in even coarse seasonal rainfall totals, are also unclear (Rowell and Chadwick 2018).

We define the concept of *climate tracking* as the alignment or skill of smallholder observations over time relative to climatic processes, namely rainfall. Better climate tracking should support improved on-farm decisions and livelihood security (Crane et al. 2011). While intuitive, this hypothesis remains untested empirically in regions of limited scientific climate information and where barriers exist for farmers to utilize climate tracking knowledge through adaptive responses on their farm, such as through technological changes (Adger et al. 2003; Boko et al. 2007; Nakashima et al. 2012; Waldman et al. 2019a).

Here, we test the hypothesis that skillful farmer climate tracking is associated with higher farm productivity in multiple sites across western Uganda (Fig. 1a). Our approach assumes that individual-level climate tracking skill can enable improved farm management, mediated through farmers' capacities and institutions (Crane et al. 2011). To test our hypothesis, we estimate Bayesian multilevel statistical models fit to multisite farm-level data on primary crop yields (e.g., maize, beans, potatoes), climate tracking, and controls (n = 614). Tracking measures are based on recalled farmer perceptions of dekadal, or 10-day, rainfall occurrence over a general year (i.e., presence–absence in beginning/middle/end of months), during recent (i.e., the past few years) and past (i.e., 10–20 years) time periods. Correlation coefficients are then calculated associating dekadal farmer observations with mean dekadal rainfall estimates from validated satellite-based data products, 2014–18 and 1998–2008 (Funk et al. 2015; Maidment et al. 2017; Diem et al. 2019a).

2. Methods

We evaluate the hypothesis that farmer-level skill of rainfall observations over time (i.e., tracking) is associated with higher agricultural yields. Our approach to measure tracking assumes the importance of seasonal rainfall timing in our agricultural system and that past experiences inform current on-farm behavior (Crane et al. 2011; Orlove et al. 2010; Salerno et al. 2019). We define tracking as the correlation between recalled farm-level observations of seasonal rainfall timing (in recent 1–4 years and 10–20 years in the past) measured through both household surveys and dekadal rainfall estimates (2014–18 and 1998–2008) from multiple validated satellite-based rainfall products (Funk et al. 2015; Maidment et al. 2017; Diem et al. 2019a). The sections below describe the study region, household survey data and processing, climate data and processing, and statistical analyses.

Research protocols were approved by the University of Colorado Institutional Review Board (14–0145) and the Uganda National Council for Science and Technology and Research Ethics Committee (NS37ES). Research design, conduct, and data collection proceeded following recognized ethical guidelines (American Anthropological Association 2012; Brittain et al. 2020). Prior to conducting research, local permissions were granted at the level of the LC1 (i.e., village). All research participants gave prior informed consent.

a. *Study region*

Western Uganda is located in a climatological transition zone between central and eastern equatorial Africa. Mean annual precipitation ranges from ∼1100–1400 mm, but with appreciable interannual variation (Salerno et al. 2017). Annual rainfall in western Uganda is generally higher than in Kenya to the east (Nicholson 2017) but lower than in the Congo Basin to the west (Todd and Washington 2004). Seasonal rainfall patterns vary markedly, with the far northern portion of the region experiencing a near-annual rainfall regime (i.e., rains occur as one long season from late March to mid-November), while the rest of the region experiences a biannual rainfall regime with the one rainy season typically occurring from March to mid-May and another occurring from August to early December (Diem et al. 2019b). In contrast to eastern equatorial Africa, the rains during boreal spring are colloquially known as the short rains, and the rains during boreal autumn are known as the long rains (Hartter et al. 2012; Diem et al. 2017).

This study reports data from a larger research effort aimed at understanding atmospheric controls of rainfall in western Uganda (Diem et al. 2019a,b). Therefore, site selection for household data collection was informed by the location of rainfall zones spanning the latitudinal range of the study region, with study communities purposefully selected at the northern- and southernmost extent. We refer to these sites as Masindi and Bwindi, respectively.

Rainfed smallholder farming systems characterize the study region, with farmers employing relatively few mechanical and chemical inputs in diversified cropping strategies (Hisali et al. 2011; Okonya et al. 2013; Salerno et al. 2017). In the northern site, Masindi, farmers grow predominantly maize during a single growing season, though multiple harvests are possible depending on rainfall. In the southern site, Bwindi, farmers grow a variety of crops, including potatoes, beans, sweet potatoes, maize, millet, tomatoes, and cassava over multiple harvest cycles annually.

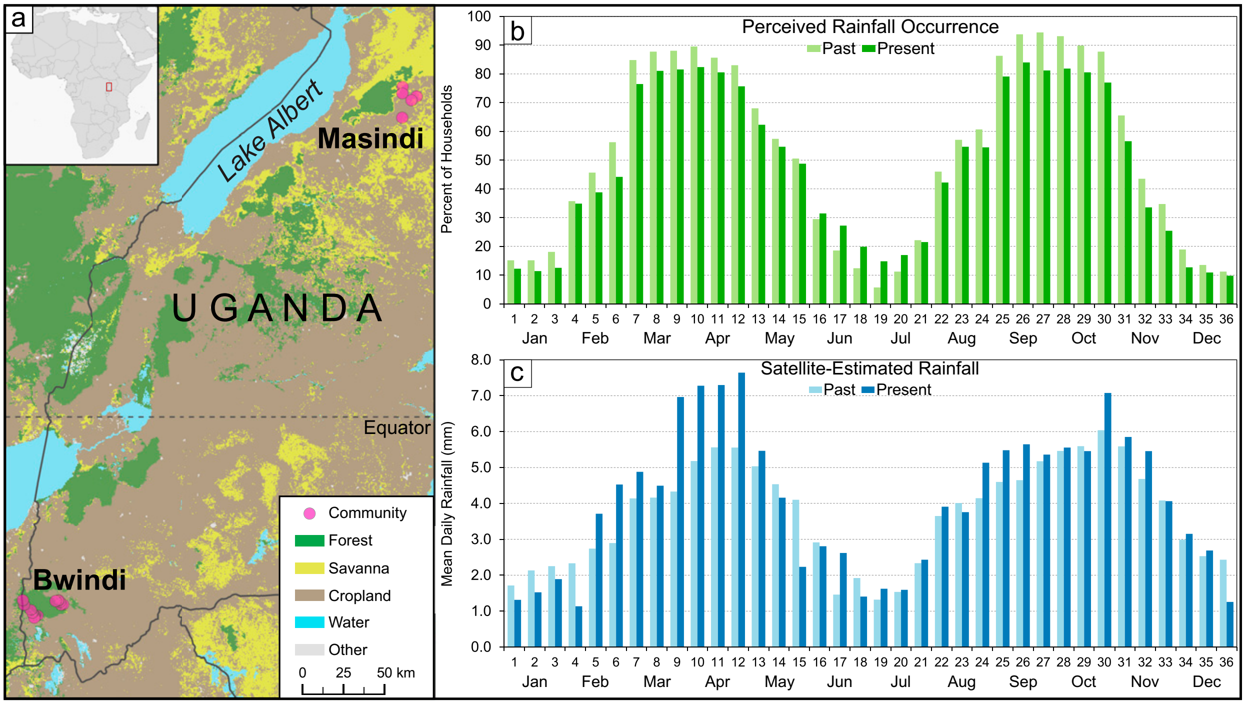

FIG. 1. Intra-annual seasonal rainfall patterns in western Uganda. (a) Study region in the climatic transition zone of eastern and central equatorial Africa, land cover (Friedl et al. 2010), and locations of study communities in the northern and southern sites. (b) Percentage of farmer respondents (n = 614) observing rainfall presence (1/0) in 36 dekadal periods (January–December), reported through surveys, and corresponding to recent (last few years) and past periods (10–20 years). (c) Mean total rainfall (mm) averaged across Masindi and Bwindi sites in 36 dekadal periods (January–December); data represent mean values from two validated satellite-based rainfall products in recent (2014–18) and past periods (1998–2008) (Funk et al. 2015; Maidment et al. 2017). See Fig. S1 in the online supplemental material for higher-resolution longitudinal comparisons of rainfall and temperature.

Because rainfall timing is highly variable, crop selection and planting time represent critical farm management decisions. In such systems with variable rainfall, and where scientific forecasts are unreliable or inaccessible, local knowledge of spatial and temporal patterning of rainfall becomes essential (Haile 2005; Roncoli 2006; Simelton et al. 2013; Kassie et al. 2013; Fassnacht et al. 2018). Indeed, farmers elsewhere in Uganda integrate historical knowledge, environmental signs such as changing weather or bird migrations, local variation, and information shared through social networks in order to make on-farm decisions (Orlove et al. 2010; Roncoli et al. 2011). Uganda's Vision 2040 and national strategy for climate adaptation emphasize improving accuracy and accessibility of forecasts (Republic of Uganda 2007, 2020; Echeverría et al. 2016). However, rainfall forecasts are coarse in spatial and temporal resolution, usually downscaled to one or multiple regions and disseminated semiannually, and farmers can find them of varying utility (Patt et al. 2007; Okonya et al. 2013; Mwangu 2020; Osbahr et al. 2011).

b. *Household data*

Household survey and focus group data were collected in the Bwindi and Masindi sites after the first harvest in 2018 and 2019. Field work activities were conducted using the languages of Runyoro in Masindi and Rukiga in Bwindi. We conducted focus group interviews to obtain qualitative data from farmer participants on rainfall related to livelihoods and to refine the household survey for local relevance and validity.

Household surveys were conducted by trained enumerators in 30–50 randomly selected households in each community. Randomization was implemented using village and subvillage rosters with support from village (LC1) leaders. At each household, surveys were requested with the head of household or spouse responsible for farming and farm management decisions; it was typical for multiple adult family members to participate jointly in surveys. We acknowledge the possibility that family members may hold different views of rainfall based on different roles and experiences, for instance, along gender lines. We nevertheless hold that the randomized sampling frame, presence of male and female primary respondents in the sample, and collaborative household nature of surveys limit such biases. Surveys recorded data on rainfall observations and farm livelihoods.

For main analyses in this study, we use a suite of household-farm variables drawn from the survey. The purpose is to build a controlled model predicting crop yields and assess whether skillful climate tracking serves as an informative predictor along with a robust set of controls. Crop yield is our outcome variable, which we standardize across crop types because households typically plant multiple crops over multiple seasons, and because fields are often intercropped. In relation to climate tracking, we assume farmers continuously make weather and rainfall observations, update their expectations about timing and amount, and apply this information to specific crops and plots (Crane et al. 2011; Orlove et al. 2010), although we acknowledge that perceptions of rainfall may be sensitive to crop type. Yield is estimated from household survey responses reporting crops grown (predominantly potatoes, beans, sweet potatoes, maize, cassava, millet), area of land on which crops were planted, and total amount harvested. We standardized yield calculations as the value of harvested crops in Ugandan shillings (UGX) per hectare. Crop value was determined by the crop price paid in the nearest trading center during the survey period (at previous harvest time) based on key informant and focus group interviews. Units of the amount harvested for each crop were converted to kilograms, area planted was converted to hectares, and market price was applied to produce yield estimates in UGX per hectare; 585 farmers reported sufficient data with which to calculate primary crop yields.

Perceptions of recent and past rainfall timing in a general year were recorded using a combination of verbal and visual questioning. To record recent rainfall observations, respondents were asked, "In the last few years, when is it normal for rains to fall?" Enumerators contextualized the question relative to the seasonality of rainfall (i.e., terminology was used for the first/short rains and the second/long rains specific to the sites). During focus group discussions and pretesting, farmers indicated that referring to the beginning, middle, and end of each month was meaningful to them for recall of previous rainy seasons. Similar studies investigating recall of rainfall timing in previous years have used similar time periods in questioning (Waldman et al. 2019b). Therefore, surveys prompted respondents to point to monthly boxes (arranged in a line representing a calendar year) with the aid of the enumerator to indicate when they recalled appreciable rainfall; respondents specified divisions within each monthly box corresponding to the beginning, middle, and end of each month (i.e., 10-day dekad). Respondents were encouraged to interpret what they considered appreciable or meaningful rainfall to be in the context of their farms and rains that inform decisions or motivate management action. Responses produced 36 presence/absence (yes/no) responses corresponding to dekadal periods. To record past rainfall observations, respondents were asked, "In the past, perhaps ten to twenty years ago or when you were a child, when was it normal for rains to fall?" This question yielded a second set of 36 dekadal rainfall presence/absence responses.

Studies from smallholder systems have shown that recall bias can exist, for instance, where farmers perceive past rainy season onset becoming later while station- or satellite-based estimates show no clear trend (Simelton et al. 2013; Osbahr et al. 2011; De Longueville et al. 2020). Such discrepancy can be due simply to poor recall or memory, or due to cognitive biases related to how farmers process past information and patterned by individual livelihood or social factors (e.g., age, education, local narratives) (Waldman et al. 2019b; Mulenga et al. 2017). However, our study does not assume that farmer rainfall responses are free of recall bias, only that the variation in measured perceptions of rainfall timing reflects the relative skill of respondents in recalling this information. In addition, in part because farmers use heuristics to recall previous rainfall information, responses may be less attentive to interannual variability or distinguishing between total amount and timing of rain (Waldman et al. 2019b). While our questioning focuses on timing of rainfall alone due to its central importance for yields in the sites, a point borne out by focus groups and studies from the larger region (Osbahr et al. 2011; Cooper et al. 2008), the tracking measures are less attentive to and perhaps conflated with rainfall amount. Moreover, responses could have been influenced by enumerators' normative beliefs in terms of "correct" rainfall timing, but enumerators were carefully trained to simply explain the questions, present the tables representing annual patterns, and record rainfall presence where respondents indicated. Despite the complex questioning and potential for biases associated with our tracking measure, we feel that appropriate steps were taken to minimize such biases, and the potential for impacting our suggested findings is small, particularly given the exploratory nature of this study. Nevertheless, given the possibility of inaccurate recall, we are cautious with asserting our findings.

In addition to yield and tracking, we draw additional variables from the household surveys with which to build statistical models to control for variation in yield outcomes, including household demographic, individual, and farm-level covariates. We include respondent age, respondent level of education, whether the household had lived in the site for more than 10 years, number of individuals in the household, farm size at present (ha owned), whether the household fallowed any land in the previous year, whether the household rented farmland in the previous year, whether the household used fertilizer in the previous year, whether the household used mulch or similar soil amendments in the previous year, whether the household owned cattle in the previous year, and whether the household owned goats, sheep, or pigs in the previous year. Model specification is described below, and descriptive means of household variables are presented in Table S1 in the online supplemental material.

c. Rainfall data

Diem et al. (2019a) found that two satellite-based products, Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and Tropical Applications of Meteorology Using Satellite and Ground-Based Observations (TAMSAT), have minimal temporal biases and do not produce artificial drying trends like those seen for other products (e.g., African Rainfall Climatology, version 2). Without temporal adjustments, both products have significant temporal correlations (i.e., annual totals from 2000 to 2012) with ground-measured rainfall totals in western Uganda (Diem et al. 2019a). Therefore, daily rainfall estimates for 1983–2019 from version 2 of CHIRPS (Funk et al. 2015) and version 3 of TAMSAT (Maidment et al. 2017) were used in this study. Those data were obtained from the

International Research Institute for Climate and Society at Columbia University. CHIRPS and TAMSAT have spatial resolutions of 0.05° and 0.0375°, respectively, and begin in 1981 and 1983, respectively. CHIRPS was serially complete, while TAMSAT was missing 5% of daily rainfall totals. For each of days with missing data, the mean value for the day of year—over the 37 years—was used as the predicted rainfall total for the TAMSAT product. Monthly temperature data from The Berkeley Earth Land/Ocean Temperature Record (Rohde and Hausfather 2020) were also accessed to assess alongside rainfall products and are presented as simple site-specific trends in the online supplemental material.

d. Derivation of climate tracking

The individual-level skill of farmer climate tracking was represented by the point-biserial correlation coefficients between a farmer's perceived rainfall occurrence, a set of binary variables, and satellite-estimated rainfall totals, a set of continuous variables. Point-biserial correlations are appropriate for use with binary and continuous data (Sheskin 2020). Correlations were computed from vectors of 36 values, each value specific to a dekadal, or 10-day period. Farmers identified these presence–absence rainfall values in each dekad relative to "in the last few years" and "10–20 years in the past"; see above description under household data. The associated dekadal rainfall total was the mean of the estimates from the CHIRPS and TAMSAT gridded products corresponding to the nearest pixels to each household; values for both Masindi and Bwindi were derived from the nearest 15 CHIRPS cells and 25 TAMSAT cells. Derivation resulted in a range of correlation values (Fig. S3 in the online supplemental material), including a small number of near-0 values, perhaps indicating misunderstanding of questioning in isolated cases.

As noted in the results and discussion sections (sections 3 and 4), we use a literal interpretation of previous rainfall periods from the survey questions against which to assign satellite-based rainfall estimates and calculate recent and past tracking correlations specific to each farmer (2014–18 and 1998–2008). We acknowledge that farmers may not interpret their perceptions of previous periods as precisely aligned with these recent and past periods. We therefore explore the sensitivity of tracking derivations to the selection of recent and past periods of satellite-based rainfall data by varying the start and end years as follows in relation to the periods stated in the survey: for recent tracking, 2014–18, 2015–18, and 2016–18; for past tracking, 1983–2008, 1983–2013, 1988–2008, 1988–2013, 1993–2008, 1993–2013, 1998–2008, 1998–2013, 2003–08, and 2003–13. Boxplots of these different tracking derivations show almost no sensitivity to the varying periods of rainfall data used (Fig. S5 in the online supplemental material). To further test sensitivity, we fit models using each of these alternative tracking derivations. Coefficient estimates of the tracking effects are nearly identical regardless of time period, with recent tracking as a credible predictor of yield outcomes across all models (Fig. S4 in the online supplemental material; models are detailed just below).

e. Statistical analysis

To assess the association between accuracy of climate tracking and farm yield, we fit a Bayesian multilevel statistical model to farmer-level survey data and farmer climate tracking variables. The log-transformed outcome variable, crop yield, approximates a normal distribution, informing the use of a Gaussian model structure. We estimate the model using Hamiltonian Monte Carlo procedures in Stan, called through the R Statistical Environment (v.4.1.0) (R Core Team 2020) via {rstan} (v2.26.1) (Stan Development Team 2021) with the map2stan() function of the {rethinking} package (McElreath 2015).

The Gaussian model is fitted to the 585 household observations where yield is observed. Data are structured as households in communities (i.e., villages), parishes, subcounties, counties, and districts within each site (see sample description, above); trading center is the relevant level of organization above community within which farmers interact. Varying intercept parameters are included for communities and trading centers. These varying effects capture unobserved variation in yield outcomes (i.e., spatial nonindependence or clustering of the data) based on biophysical, agroecological, institutional, or other place-based factors.

The formal model is specified as

$$y_i \sim \mathrm{Normal}(\mu_i, \sigma), \text{ with}$$

$$\begin{aligned}\mu_i = \alpha &+ \alpha_{\mathrm{c}(i)} + \alpha_{\mathrm{s}(i)} + \beta_{\mathrm{recent}} r_i + \beta_{\mathrm{past}} p_i + \beta_{\mathrm{age}} a_i + \beta_{\mathrm{ed}} e_i \\ &+ \beta_{\mathrm{resident}} n_i + \beta_{\mathrm{household}} h_i + \beta_{\mathrm{farm}} f_i + \beta_{\mathrm{fallow}} d_i \\ &+ \beta_{\mathrm{rent}} l_i + \beta_{\mathrm{fert}} k_i + \beta_{\mathrm{amend}} m_i + \beta_{\mathrm{cattle}} c_i + \beta_{\mathrm{medstock}} g_i,\end{aligned}$$

where farmer-level yield y_i is defined by a Gaussian distribution with mean μ_i and standard deviation σ; α is the grand intercept, $\alpha_{c(i)}$ is the varying intercept for each community, and $\alpha_{s(i)}$ is the varying intercept for each subsite (trading center); β_{recent} is the effect of recent climate tracking r_i; β_{past} is the effect of past climate tracking p_i; β_{age} is the effect of age a_i; β_{ed} is the effect of the binary indicator for having completed secondary school or higher e_i; $\beta_{\mathrm{resident}}$ is the effect of the binary indicator for living in the area for more than 10 years n_i; $\beta_{\mathrm{household}}$ is the effect of household size h_i; β_{farm} is the effect of farm size f_i; β_{fallow} is the effect of the binary indicator for fallowing farm land d_i; β_{rent} is the effect of the binary indicator for renting farm land l_i; β_{fert} is the effect of the binary indicator for applying fertilizer k_i; β_{amend} is the effect of the binary indicator for using soil amendments or mulch m_i; β_{cattle} is the effect of the binary indicator for owning cattle c_i; and $\beta_{\mathrm{medstock}}$ is the effect of the binary indicator for owning medium livestock g_i.

Priors on all farmer-level fixed effects are Gaussian, with mean of 0 and standard deviation of 1. Priors on all varying intercept effects are Gaussian with mean of zero and variance hyperparameters; priors on hyperparameters are half-Cauchy with location of 0 and scale of 1. The model is coded and estimated following published methods (McElreath 2015).

The following transformations are used for model variables: log of yield (UGX per hectare), log of age (years), log of

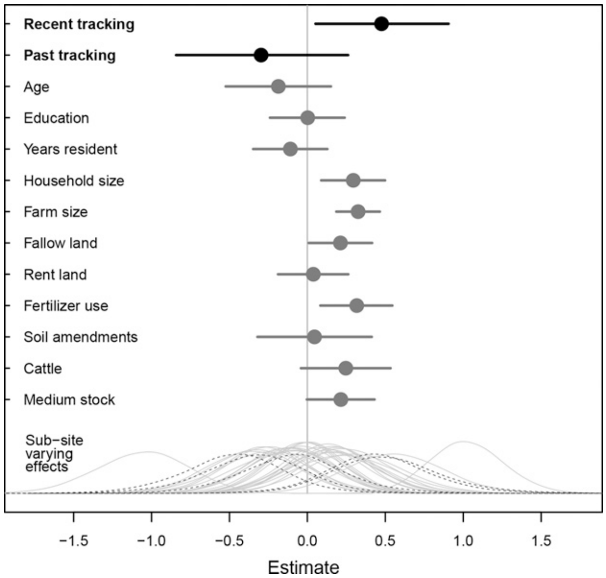

FIG. 2. Coefficient estimates from the multilevel statistical model predicting farm yield. Farmer-level posterior mean estimates (and 95% credibility intervals) include climate tracking effects corresponding to recent (2014–18) and past periods (1998–2008) along with control covariates. Varying intercept (i.e., random) effects at the community (light-gray solid curves) and subsite (light-gray dashed curves) levels are plotted as overlapping densities and represent place-specific adjustments (and uncertainty) to the grand intercept, controlling for spatial nonindependence of reported yields. All estimates are drawn from the joint-posterior density of the Gaussian multilevel statistical model.

household size (number of people), and square root of farm size (ha). All other variables are retained on their original scale. Covariance of model variables is examined for multicolinearity; values are presented in Table S2 in the online supplemental material.

Model estimation is computed with a 10 000-iteration burn-in and 10 000-iteration posterior sample on an Intel Xeon E5 3.6 (4.5) GHz 8-core processor, with 64 GB of memory, running macOS, version 10.15.6. Examination of traceplots and kernel densities indicate adequate mixing. Additional model diagnostics are performed by examining R-hat (i.e., potential scale reduction statistic to evaluate convergence) and n_eff (i.e., crude estimate of independent samples of parameters to evaluate uncertainty) values, and by conducting posterior predictive checks (McElreath 2015). Together, these diagnostic steps indicate appropriate model fit.

We evaluate our central hypothesis that skill in farmer-level climate tracking is associated with higher yields by presenting graphical and tabular summaries of posterior densities of household-level fixed effects estimates and varying intercept effects estimates (Fig. 2; Table S3 in the online supplemental material).

3. Results

Raw data from farmer recalled observations align generally with the timing and duration of seasonal rainfall patterns indicated by satellite-based estimates, with farmers reporting notable differences between past and present rainfall patterns (Figs. 1b,c). In aggregate across the two sites, farmers are more confident in the presence of distinct bimodal rainfall patterns one or more decades in the past than in the recent several years (Fig. 1b). While not evident in these coarse contrasts (Fig. 1c), trend analyses of satellite-based data corroborate this weakening of the bimodal regime, in particular through increasing rainfall during the boreal summer dry seasons (Fig. S1 in the online supplemental material; also Diem et al. 2019b). Importantly, there is appreciable variation in observations of rainfall patterns among farmers both within and between sites, and so likewise in our climate tracking measures, indicating a range of skill across farmers (Figs. S2 and S3 in the online supplemental material).

The statistical model shows that skillful climate tracking of rainfall timing in recent years credibly predicts higher crop yields in the present [Fig. 2; posterior mean, 0.48, 95% credibility interval, (0.05, 0.91)]. The model estimates this effect in the presence of farm-level covariates (e.g., land holdings, education, on-farm practices) that we expect a priori to pattern yields. The model also accounts for yield differences at community and subsite levels that control for varying agroecological conditions and other place-based features like quality of regional forecasts. Notably, only two community-level (and no subsite-level) effects are credibly different from 0, meaning much of the variation in yields is explained by farmer-level factors. Results lend support to our hypothesis that farmers who more skillfully observe and recall recent rainfall patterns experience higher crop yields, which we infer from the controlled model to potentially be mediated by on-farm adaptive practices. More skillful tracking of past rainfall, on the scale of one to two decades, is not credibly associated with higher or lower crop yields [−0.30 (−0.84, 0.26)]. This latter result—that perception of past climate patterns does little to inform higher yields today—is congruent with historical knowledge systems losing their predictive power in a region with changing rainfall patterns and limited access to actionable scientific forecasting (Osbahr et al. 2011; Roncoli et al. 2011; Okonya et al. 2013) or may suggest the presence of biases in recall (Waldman et al. 2019b). We discuss these possibilities further below.

The association of more skillful recent climate tracking with present yield is robust to various derivations of tracking variables. Here in the main text, we report model results and tracking measures determined by a literal interpretation of recent and past periods from surveys: 2014–18 (recent as "the last few years") and 1998–2008 (past as "10 to 20 years or more in the past"). We also conduct a sensitivity analysis by varying the range of years selected from satellite-based data used to calculate tracking correlations. The model-estimated coefficients (and credibility) are consistent across this range of tracking derivations (Fig. S4 in the online supplemental material). We discuss the tracking derivation further below.

Observed farmer tracking and crop yield outcomes likely occur against a backdrop of changing climate in the region. Assessing these background conditions, we show that monthly mean temperatures have increased over all months of the year in both sites since 1983 (Fig. S1 in the online supplemental material). Mean monthly rainfall has increased at one or both sites during the first rains (March–mid-May), the intervening boreal summer dry period (mid-May–July), and during the early period of the second rains (August–November). Such wetting trends are evident throughout western Uganda, likely caused by increased atmospheric moisture and instability (Diem et al. 2019b). Ongoing changes in temperature and rainfall highlight the importance of local knowledge in adapting to variable and changing climate, particularly because scientific forecasts can be unreliable and variably interpreted (Roncoli et al. 2011; Okonya et al. 2013).

4. Discussion

Our results suggest the likelihood that some farmers can skillfully observe and adapt to variable and changing climate. These results have mixed implications. While intra-annual variation in recent rainfall is pronounced, some farmers may accurately observe this variation and update their expectations to inform selection of crops, timing of planting and harvest, and other on-farm strategies (Okonya et al. 2013; Salerno et al. 2019; Guido et al. 2020), which we infer are linked to the model-estimated increase in yields. Indeed, farmer knowledge systems have evolved to be flexible and inform critical decisions to support livelihood resilience (Orlove et al. 2010; Crane et al. 2010). However, we observe a range of tracking and yield values in our study region (Fig. S3 and Table S1 in the online supplemental material), suggesting that many farmers may not have observed recent rainfall patterns in ways that inform present on-farm decisions, or that barriers to adaptive capacity exist to limit utility or salience of this information (e.g., high cost of short-cycle seed, uncertain efficacy of altered practices) (Hisali et al. 2011; Waldman et al. 2019a). Such limitations pose notable sustainability challenges in a nation of 70% smallholder farmers, with an uncertain and changing climate, and with projected total population growth among the world's highest (Salerno et al. 2017).

Our approach and findings represent a departure from the majority of sustainability research assessing alignment between smallholder climate observations and scientific climate measures (Savo et al. 2016; De Longueville et al. 2020), both by reporting what can be interpreted as accurate recall and by associating this recall with on-farm outcomes. In general, published research compares largely qualitative measures of farmer observations with physical records and shows inconsistent alignment of rainfall totals, timing, variability, and trends (Roncoli 2006; Osbahr et al. 2011; Simelton et al. 2013; Mulenga et al. 2017; De Longueville et al. 2020), though with notable exceptions (Chaudhary and Bawa 2011; Savo et al. 2016; Salerno et al. 2019). Reasons for misalignment focus on spatiotemporal mismatch between climate records and farmer observations, perceptual or recall biases, and smallholder knowledge systems integrating diverse information sources (e.g., soil moisture, crop and range productivity, local and nonlocal kin networks) that may influence rainfall or temperature interpretation (Orlove et al. 2010; Osbahr et al. 2011; Simelton et al. 2013; Waldman et al. 2019b).

In regions of limited scientific climate data, and where the skill and salience of scientific forecasts is uncertain for many farmers, local observations may augment patchy climate records and support scientific seasonal forecast creation and uptake (Chaudhary and Bawa 2011; Roncoli et al. 2011; Savo et al. 2016). We highlight the importance of examining smallholder climate observations in the context of livelihood outcomes, in our case yields, and focusing on farmer agency. Indeed, decisions and their skill result from farmer experiences over time, influenced by social and ecological processes, and translated variably by individual farmers (Crane et al. 2011).

a. *Limitations and future applications*

Our analysis estimates a credible association between skillful climate perceptions and yields. These findings rest on the key assumption of intervening mechanisms of adaptation, which are likely complex and variable (Roncoli 2006; Crane et al. 2011; Okonya et al. 2013). However, we do not control for all possible confounds, such as kin relationships or embeddedness in knowledge networks, which could indeed influence both tracking skill *and* yield outcomes. If such unmeasured factors were the true adaptive pathway to improved yields, our estimated effects of rainfall tracking on yield could be spurious. Future work should interrogate the stated assumption linking climate information to on-farm actions to outcomes using robust data and causal models (Ferraro et al. 2018). Despite this caveat, our findings are consistent with previous reports of farmers integrating meaningful observations into dynamic knowledge systems that inform plot-specific on-farm strategies (Orlove et al. 2010). For instance, challenging decisions such as when and what varieties to plant and harvest likely require pooling of information from social and environmental signals (including perceptions of rainfall timing), but optimal decisions can indeed directly impact higher crop yields (Crane et al. 2011; Akinnuoye-Adelabu and Modi 2017; Waldman et al. 2019b).

Our measure of farmer climate tracking is a correlation coefficient between recalled rainfall observations and satellite-based rainfall estimates, both of which are subject to error. For example, recall error may exist because of cognitive biases shaped by uncertainty and shared narratives about climate change, which can limit farmers' identification of previous rainfall seasonality (Mulenga et al. 2017; Waldman et al. 2019b). However, our approach assumes a range of tracking (recall) skill present in our sample, which is evident in the data, and our goal is to assess whether relatively higher skill is associated with higher yields, while limiting patterned bias through a controlled model. Importantly, our analyses aim to measure within-region variation in tracking skill, rather than determine whether farmers in general are skilled or not. Moreover, we implement steps to minimize measurement error through grounding climate recall methods in locally specific seasonality, while narrowly focusing survey questions on timing (not amount) of seasonal rainfall (Roncoli 2006). Farmer responses are then associated with validated satellite-based rainfall products (Diem et al. 2019a), which are appropriate for our aims due to the paucity of rain gauge data (Kizza et al. 2009). Further details are provided in the methods section (section 2), but issues of bias, measurement, cognition, and skill should remain central to future research on climate perceptions and decision-making.

Similarly, as noted in the results presented above, we use a literal interpretation of previous rainfall periods from the survey questions against which to assign satellite-based rainfall estimates and calculate recent and past tracking correlations specific to each farmer (2014–18 and 1998–2008). In part because of recall and cognitive biases just noted, farmers are unlikely to average over the exact periods in question to report rainfall patterns precisely aligned with corresponding satellite-based rainfall years. We therefore conduct a sensitivity analysis by varying the periods of recent and past rainfall estimates used in calculating tracking coefficients (Fig. S5 in the online supplemental material). We fit 30 models with identical structure to the model presented in the main text, except with recent and past tracking variably defined. All models estimate nearly identical tracking effects and credibility (Fig. S4 in the online supplemental material), suggesting that the association between recent tracking and higher yields is robust to the selection of rainfall periods.

b. Conclusions

Going beyond simply assessing agreement or accuracy of smallholder observations and scientific measures, our findings are unique in associating more skillful farmer-level tracking of rainfall patterns with higher agricultural yields, which suggests the likelihood of adaptive capacity in some households and a degree of resilience to rainfall variability. These findings are relevant to smallholder farming systems poised to experience profound impacts of demographic and climatic change (Alexander et al. 2011). By interrogating the assumption that better climate information supports smallholder adaptive capacity, we articulate an urgent need and recommend that improved climate science and seasonal forecasting directly engage with local knowledge systems in the creation and dissemination of climate information (Crane et al. 2011; Simelton et al. 2013; Savo et al. 2016). Such engagement should be better integrated into relevant policy and adaptation fora at national and international scales (Carr et al. 2020; World Meteorological Organization 2011; Republic of Uganda 2020).

Acknowledgments. Funding was provided by the U.S. National Science Foundation (1740201) and National Geographic Society (CP-R003-17, 9914-16). We are grateful to the respondents and community leaders that participated in and enabled this research. For their skill and support in data collection, we thank Tinkasimire Rogers, Phillemon Tumwesigye, Nick Dowhaniuk, Atusasiire Eriab, Ayiretse Lota, Mujuni Robert, Nkiosibwe Aventino, Owoyesigire Narsensio, Alinaitwe Job, Allan Karim, Ayebale Brian, Immaculate Alinaitwe, Ritah Nabankema, and Tumusime Amos. Dr. Carla Roncoli provided valuable comments on earlier drafts of the paper.

Data availability statement. Summary data supporting findings and conclusions are available within the paper and the online supplemental information. Rainfall and temperature data are cited within the paper. Deidentified household data to reproduce analyses are available from the authors.

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