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Is this land for sale? The effects of drought on land ownership in Uganda

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ABSTRACT

This study examines the impact of drought on the land ownership rights of smallholder farmers in Uganda. Three waves of the Uganda National Panel Survey are combined with an indicator for drought, the Standardized Precipitation Evapotranspiration Index. Using a household fixed effects approach, we exploit spatial and temporal variation in drought conditions to identify its effect on households' self-reported willingness to acquire land ownership rights, both at the extensive and intensive margins. Results show that exposure to drought lowers households' intentions to purchase land and substantially reduces the price households are willing to pay for land. The effects persist over time and are robust to different specifications. Our findings suggest that drought exposure limits the operating space for farmers wishing to purchase land.

1. Introduction

When a disaster hits, households in low-income settings can be forced to sell their productive assets (Khandker, 2007; Lawson and Kasirye, 2013; Longhurst, 1986; Nguyen et al., 2020). Distress sales of livestock and land are documented as a strategy of last resort by smallholder farm households to cope with shocks (Corbett, 1988; Deininger and Jin, 2008; Helgeson et al., 2013; Holden and Otsuka, 2014). But how do shocks affect the intention of households to purchase land in potentially risky environments? We study this question in the context of drought. Our focus is on Uganda, where many households hold use rights to land and face the decision of whether to acquire full ownership rights to this land. Specifically, we explore whether exposure to drought affects the willingness of farmers to purchase land ownership rights and the price they are willing to pay for it.

Interest in households' formal land tenure is dominating the academic debate on property rights to land and agricultural productivity. Much less is known on more volatile and sometimes short-term use rights to land.[2] Specifically, little is known about those factors that shape farmers' willingness to convert such use rights into full-fledged ownership rights. While distress land sales are widely studied (Helgeson et al., 2013; Holden and Otsuka, 2014; Musyoka et al., 2021), potential effects of weather shocks and climatic conditions on land purchases and, more broadly, on land tenure have received much less attention. Generally, the literature on the impact of extreme weather events emphasizes *ex post* coping mechanisms, such as the role of savings, migration, consumption reduction, and asset sales, but has less to say on asset accumulation in the face of weather shocks, in particular with regard to land (an exception is Kinsey et al., 1998).

Uganda is an interesting case study for analyzing land purchase decisions because use rights to land are wide-spread (Deininger and Ali, 2008; Musinguzi et al., 2021). For many farmers, this naturally raises the question of whether to convert land use rights into full ownership rights. At the same time, according to the global index on vulnerability to climate change, Uganda is one of the countries most vulnerable to climate change (ND Gain, 2019). Both frequent and severe droughts and floods plague the country, with notable droughts occurring in 2005, 2008, 2009/10, and 2017. The 2009/10 drought was particularly severe, affecting more than half of the country's area (Kyatengerwa et al., 2020). Droughts are projected to occur more frequently and increase in intensity with increasing climate change (Spinoni et al., 2020).

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2 An exception is sharecropping, a specific form of land use rights that is widely studied (Burchardi et al., 2019; Shaban, 1987). Other common types of use rights include (short-term) rentals or agreements within the family.

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Our analysis builds on three waves of the Uganda National Panel Survey (UNPS), collected between 2005 and 2011, which we combine with high-resolution precipitation and temperature data, from which we calculate the Standardized Precipitation Evapotranspiration Index (SPEI). The SPEI is a drought index that expresses dry conditions in standard deviations from the mean water balance in a given location. The UNPS records land ownership and land use rights in great detail, making the panel data a unique source to provide novel evidence on this topic. Our identification strategy exploits spatial and temporal variation in drought conditions, using a household fixed-effects approach to account for time-invariant household characteristics.

We contribute to the literature in three ways: First, our study provides novel evidence on the effects of drought on households' intentions to purchase land, a subject that has not been – to the best of our knowledge – previously studied. We estimate the effect of drought on land purchase intentions both at the extensive margin (whether a household intends to buy ownership rights at all) and the intensive margin (the amount a household is willing to pay), providing a detailed account. Second, as we study the effect of extreme weather on the price that households are willing to pay for land, we contribute to the debate on the impacts of weather and climate on the value of farmland. This literature mainly focuses on longer-term climate effects on farmland value in the Global North, using Ricardian approaches (Bozzola et al., 2018; Lippert et al., 2009; Mendelsohn et al., 1994). Yet, little is known on how extreme weather affects the value of farmland in low-income countries. A third innovation of our study lies in the use of high-resolution gridded weather data ($0.05° \ x \ 0.05°$) to calculate the SPEI. Such high-resolution data better capture local climatic conditions and extremes than data sets with lower resolution that are otherwise commonly used in econometric assessments of weather impacts (e.g., Cui and Xie, 2022; Koo et al., 2021; Von Uexkull et al., 2016).

Results show that negative SPEI values – indicating drier than average conditions – during the current crop growing season significantly reduce the willingness of households to acquire land ownership rights. An analysis of different SPEI thresholds reveals that results are driven by strong and negative effects of drought conditions: Exposure to SPEI values one standard deviation below the local average – indicating drought conditions – significantly reduces households' willingness to purchase land. Similarly, the amount households are willing to pay for acquiring ownership rights decreases when households are exposed to drought, with effects being of large magnitude. Our results have implications for adaptation and disaster risk reduction planning, as they suggest that households' land assets are affected more fundamentally by drought than commonly expected.

The study is organized as follows: Section 2 outlines the conceptual framework. Section 3 presents contextual information on land tenure and agriculture in Uganda. Section 4 introduces the data sources and main variables of interest, while the empirical framework is outlined in Section 5. Section 6 presents and discusses results as well as robustness tests. Section 7 concludes.

2. Conceptual framework

The study of land property rights is subject of major economic theories, including the evolutionary theory of land rights (Platteau, 1996), transaction cost theory (Coase, 1960), and property rights theory (Demsetz, 1974; Barrows and Roth, 1990). Most theoretical and empirical contributions in this field focus on the effects of (secure) land rights on agricultural production and investment (for reviews see Higgins et al., 2018; Tseng et al., 2021). Other strands of the literature discuss the value of different land tenure modes for coping with agricultural production risk or sharing that risk (for a review see Promsopha, 2018). Further studies discuss the efficiency of land markets in facilitating the transfer of land to its most productive user and the role of policy interventions therein Binswanger et al. (1993) and Deininger (2003).

The potential effects of climate change, extreme weather, and weather variability on land tenure receives little attention in both theoretical and empirical studies (Holden and Ghebru, 2016). In their review, Holden and Ghebru (2016) conceptualize the links between extreme weather, climate risk, food security, and land tenure systems, but focus on food security rather than land tenure as outcome. Consequently, most theoretical underpinnings for our hypotheses are drawn from related research fields that focus on food security, asset sales, and sharecropping. Kalkuhl et al. (2020) analyze the effect of climatic conditions on the prevalence of sharecropping in Sub-Saharan Africa, using a cross-sectional approach. They find mean precipitation levels, but not precipitation variability, affect sharecropping as a specific form of land tenure in several African countries. Some case studies report extreme weather destroying physical land features, such as boundary trees, and land documents, in particular paper records of formal land titles (Mitchell, 2014). Ajefu and Abiona (2020) study the mediating effects of tenure security on the impact of drought on food security in Malawi, but do not assess if tenure security itself is affected by such shocks.

Effects of climate and weather risk on land markets are documented with regard to distress land sales and rentals (Holden and Otsuka, 2014). The literature on distress land sales suggests that some households sell or rent out land in response to a shock (Musyoka et al., 2021) or when facing consumption needs (Ricker-Gilbert et al., 2019), at least when credit markets are imperfect and more so when shocks are idiosyncratic (Deininger and Jin, 2008; Promsopha, 2018). However, compared to other coping strategies, land sales take place less frequently and are often regarded as a strategy of last resort (Corbett, 1988; Helgeson et al., 2013). Opposite effects of weather on potential land purchases and land formalization are not yet studied. For high-income countries, aggregate-level effects of weather on farmland prices are documented (Bozzola et al., 2018; Mendelsohn et al., 1994; Schlenker et al., 2005), but not from the household perspective. Only a few studies analyze weather effects on farmland value in low-income countries (Hossain et al., 2020).

In the context of smallholder farm households in the Global South, we hypothesize that drought may affect households' willingness to acquire land ownership rights by lowering the value of land. On the one hand, the value of land as a productive asset depends, to a large degree, on the income that can be generated from it. The occurrence of drought may reveal to the farmer that a parcel of land is located in a vulnerable setting ill-suited for farming. This links to the Ricardian approach developed by Mendelsohn et al. (1994), which estimates climate impacts on the value of farmland as a proxy for agricultural production. In turn, decreased land value may potentially reduce households' willingness to acquire long-term ownership rights, since less income can be generated from the land.

On the other hand, households who (at least partly) access land through use rights are typically poorer on average than households owning all of their land. If households with use rights to land are more price sensitive than they are deterred by unfavorable climatic conditions, then lower land values may translate into increased willingness to acquire land. Thus, households who (at least partially) hold use rights to land may attempt to hedge against future extreme weather events with increased production. Hence, it is *a priori* unclear whether lower land value increases or decreases households' willingness to acquire ownership rights; this must be determined empirically.

3. Land tenure and agriculture in Uganda

Negative effects of climate change and extreme weather events on Ugandan farmers are documented in numerous studies (e.g., Call et al., 2019; Hisali et al., 2011; Maggio et al., 2022). The southern parts of the country are characterized by a bimodal precipitation regime, with two rainy seasons lasting from March to May and September to December, while the northeast has a single rainy season lasting

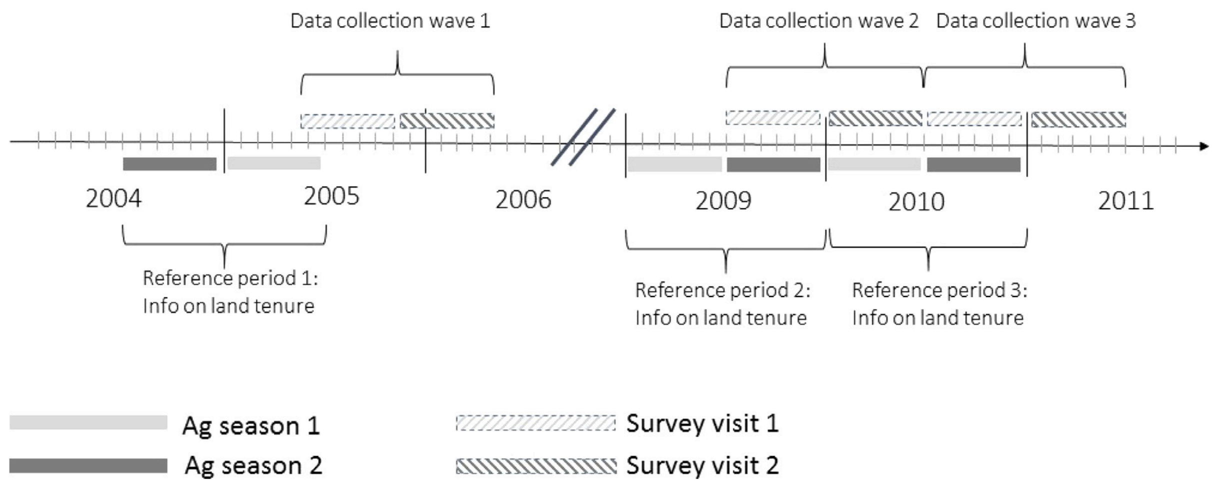

Fig. 1. Timeline of Uganda National Panel Survey.

from April to October. In southern Uganda, mainly perennial crops are cultivated, such as coffee and bananas. Precipitation is less reliable in the north and west of the country, leading to crops that tolerate lower water availability being grown, such as millet and sorghum. Maize is the dominant food crop across the country and grown in most regions, in either one or two cropping cycles. About 70% of Uganda's population was employed in agriculture in 2015 (FAO, 2015). The average farm size in 2015 was 1.35 hectare, with access to land being highly unequally distributed between men and women (UBOS, 2020) and across income groups (Owaraga et al., 2016). Only 2% of Ugandan households use irrigation, which makes precipitation critical for agricultural production (UBOS, 2020).

Land ownership and land rentals are a point of contestation and political interest in Uganda (Van Leeuwen, 2014). Land is held under an array of rules and laws, with customary and formal norms interacting and overlapping (Musinguzi et al., 2021). A key distinction runs between land that is owned and land that is held with use rights. Use rights can take the form of longer-term arrangements based on occupation rights prior to 1983, renting of land for a defined time period, sharecropping of land, or informal arrangements often of a short-term nature, such as land leased for seasonal cropping. Uganda's land tenure system comprises four main tenure types: (1) freehold tenure, which is akin to individual, private ownership of land; (2) customary tenure, under which land is often owned communally or within the family; (3) leasehold tenure, which is often periodic for 49 or 99 years; and (4) mailo tenure. The latter mainly exists in central Uganda and is a construct of the British and the Buganda kings, which in 1900 divided land measured in square miles, hence "mailo". Customary tenure is the dominant tenure type in Uganda, accounting for about 75% of its land holdings (MLHUD, 2013).

Land is increasingly under pressure in Uganda. As one of the most densely populated countries in Africa (FAO, 2014), Uganda currently sees marked population growth, with an expected population of ca. 106 million by 2050. In addition, since 2016, Uganda has been hosting significant numbers of refugees from neighboring countries (World Bank, 2020). Land close to urban centers and, in particular, in the Central region has become especially scarce.

4. Data

4.1. Household panel survey data

The data used in this study are three waves of the Uganda National Panel Survey implemented by the Uganda Bureau of Statistics in 2005/06, 2009/10, and 2010/11. The UNPS builds on the Uganda National Household Survey (UNHS) that was administered in 2005/06 and re-interviews a subset of the original UNHS sample.[3] The UNPS comprises 3123 households across Uganda. It is representative for Kampala city, other urban areas, central rural, eastern rural, western rural, and northern rural areas. The survey records detailed information on land tenure, crop production, and household demographics, as well as the exact location of the household's homestead, which allows us to match weather data from secondary sources with the household survey data. The survey separately records land ownership and land use rights, a unique feature of the data. Most land under use rights is cultivated with annual crops.

The three panel waves cover the agricultural seasons of 2004/05, 2009, and 2010. Fig. 1 illustrates the timeline of the data collection, the reference period of the land module, and the reference period of the agricultural module.[4]

We restrict the sample to rural households, as our focus is on tenure dynamics of households that primarily gain income from farming. Further, we restrict the sample to households that were engaged in crop agriculture or livestock farming, as information on land tenure was only recorded from those households. This results in a balanced sample of 1543 households for whom data is available for all three panel waves.[5] For most parts of our analyses, we focus on a sub-sample of households who hold use rights to (at least parts of) their land.

Attrition of households from the sample is a potential source of bias. In the agricultural sub-sample, of 1946 households interviewed in wave 1, 1708 and 1543 households were re-interviewed in wave 2 and wave 3, respectively. This corresponds to an attrition rate of 21% between waves 1 and 3. We conduct various tests to assess the potential bias arising from sample attrition, which are presented in

[3] Our preferred approach would have been to use more recent UNPS waves. Unfortunately, for two reasons, this is not feasible: First, survey items on households' willingness to purchase land were no longer included in the questionnaire of the fourth panel wave, collected 2011/12. Second, starting with the fifth panel wave, collected 2013/14, the UNPS replaces one third of the sample in each wave with a newly drawn refreshment sample. This drastically reduces the sample size in longitudinal analyses with household fixed effects models.

[4] Note that the reference period and survey visits differ for wave 1: Here the first visit (May–October 2005) was used to collect agricultural production data on the second agricultural season of 2004 (July–December 2004), while during the second visit (November 2005–April 2006), data was collected on the first agricultural season of 2005 (January–June 2005).

[5] Some households reported implausibly large parcel sizes. To ensure that those potential outliers are not driving the results, we excluded parcels larger than 50 acres. This cutoff is informed by the mean farm size of 1.35 ha in Uganda (UBOS, 2020).

Appendix A. Unconditional t-tests on differences in means (Table A.1 in the Appendix) across attrited households and households that remained in the panel over time do not indicate significant differences in the willingness to acquire land ownership or the amount a household is willing to pay for it. A probit regression of an indicator variable taking the value one if households are interviewed in all three waves on the controls used in our main analysis confirms this and does not show significant influences of the main dependent variables on the likelihood of staying in the panel over time (Table A.2 in the Appendix). Few variables are statistically significant and for those that are, the size of the estimated coefficients is small. To address potential bias stemming from attrition, we calculate attrition weights based on the significant coefficients and apply them to all regressions.[6]

The first outcome is derived from a survey item asking "Would you be willing to buy full ownership right to this parcel?", with the answer options being either yes or no. The first dependent variable is an indicator variable taking the value one if a household reports being willing to buy full ownership rights for at least one parcel it currently has use rights for. The survey only records this information from a subsample of households that have use rights over land at the time of the interview. This is the case for 47%, 41%, and 35% of households in the first, second, and third waves, respectively. This may introduce sample selection bias, as households that have both parcels with use rights and parcels with ownership rights (owner-cum-users) and those who solely have full ownership rights to land (owners) likely differ with regard to certain characteristics. In particular, households who own all of their land are likely to be more tenure secure than households who only farm land with use rights. In addition, land that is owned by households is likely perceived as more valuable than land that is accessed through use rights (Choumert and Phélinas, 2015). Section 6.1 discusses the differences between households with and without use rights. Since our interest is in the conversion of land use rights into land ownership rights, this sample selection does not pose a threat to our empirical strategy.

The second dependent variable captures the extent of a household's willingness to purchase land. More specifically, we use the amount of money a household is willing to pay to acquire a parcel (in Ugandan Shillings). The variable is adjusted for inflation using the Consumer Price Index (CPI), with 2010 defined as the base year. The variable is censored, as positive values are only available for households that indicated a willingness to purchase ownership rights in the first place.

Our dependent variables are derived from self-reported information on households' willingness to pay for acquiring land ownership rights. In the marketing literature, experiments are considered more advantageous than eliciting respondents' willingness to pay for a product (Breidert et al., 2006). Experiments are considered particularly useful for eliciting the willingness to pay for new or unfamiliar products (Breidert et al., 2006). This is less of an issue in our case, where surveyed households face the decision to purchase formal land ownership for parcels they already use and, presumably, know well. One potential limitation that comes with eliciting households' willingness to pay for formal land ownership is that not all households may be equally well informed about the procedures and costs of acquiring land ownership rights. In settings where both actual and self-reported intended willingness to pay is recorded from respondents, the self-reported intended willingness to pay measures are at times criticized for diverging from the actual willingness to pay (Berger et al., 2022; Reynolds et al., 2015). Overall, we consider our measure for land purchase intentions at the extensive margin the more robust measure.

Table 1 displays summary statistics for the main outcome variables by wave. On average, 40% of households in the balanced sample access some land with use rights, with considerable fluctuation across waves. About 35% of households report that they intend to acquire ownership rights at least once over the three waves.

To assess possible implications of using relatively old data, spanning the 2005–2011 window, we explore to what extent land tenure and other characteristics of Ugandan households have changed since 2011. We do so by comparing mean values in land tenure and other key household characteristics obtained from wave 3 (the last panel wave used in our analysis, collected 2010/11) with those in wave 8 (the most recently available UNPS wave, collected 2019/20). Descriptive statistics, displayed in Table A.3 in the Appendix, show that the share of households having both parcels with use rights and parcels with ownership rights (owner-cum-users) remains similar, at around 35%, in both the 2010/11 and 2019/20 waves. In contrast, the share of farmland under use rights significantly increased over time, from around 50% in 2010/11 to 58% in 2019/20. The average farm size per household significantly decreased, from 1.38 ha in 2010/11 to 1.15 ha in 2019/2020, which is in line with trends in land size of small-scale farms, rise of medium-scale farms underrepresented in household surveys, and competition over land in rural Sub-Saharan Africa (Asiama et al., 2017; Jayne et al., 2022). We conclude from those figures that our research questions and findings remain relevant in the context of (almost) present-day Uganda, as accessing land through use rights continues to be widespread. In addition, weather in Uganda has displayed a persistent drying trend over past decades (Byakatonda et al., 2021). Climate change is projected to intensify precipitation extremes in Eastern Africa (Seneviratne et al., 2021), while generally leading to unprecedented weather extremes in terms of magnitude, frequency, location, timing, and compound nature (Seneviratne et al., 2021). This makes the study of drought impacts in Uganda all the more relevant. Understanding the impacts of past weather extremes may generally provide relevant insights to better prepare against future extremes — even if each extreme event has unique characteristics and households may learn from each event.

Some socio-demographic household characteristics changed over time, with household heads being more likely to be female and educated and households more likely to receive remittances in 2019/20 compared to 2010/11. These changes reflect some general demographic and developmental trends.

4.2. Weather data

We combine the household survey data with precipitation data from the Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015) and temperature data from the Climate Hazards Center Infrared Temperature with Stations (CHIRTS) dataset (Funk et al., 2019) to calculate the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010). Both weather data products rely on comparable methods for blending weather station data with satellite data to derive gridded values of precipitation and temperature at high spatial resolution (0.05° x 0.05°, approx. 5 km in Uganda) for tropical and sub-tropical regions. They are validated for East Africa and are found to represent the local climate well (Dinku et al., 2018; Dubache et al., 2021; Verdin et al., 2020). As reference period, we use the longest available period from CHIRPS and CHIRTS data, which spans 1983–2016.

The SPEI has become a popular index to capture drought conditions (e.g., Antonelli et al., 2022; Von Uexkull et al., 2016; Harari and Ferrara, 2018). It is calculated based on the water balance between monthly precipitation and potential evapotranspiration. The SPEI is a relative measure based on the reference period's water balance and indicates water surpluses (positive values) or deficits (negative values). It represents the number of standard deviations from the normally accumulated climatic water balance for the respective location and time of the year. The SPEI has several advantages over other drought indices, such as the Palmer Drought Severity Index (PDSI) or the Standardized Precipitation Index (SPI) (Vicente-Serrano et al., 2010). For one, it uses

[6] The only exceptions are Tables D.5, D.6, and D.7 in the Appendix, since the models did not converge when including attrition weights.

Table 1
Summary statistics.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	Mean	St. Dev.	Min	Max	N
Dependent variables					
Willingness to acquire full ownership rights to land conditional on having use rights					
Wave 1	0.38	0.49	0	1	723
Wave 2	0.50	0.50	0	1	606
Wave 3	0.35	0.48	0	1	505
Amount households are willing to pay to acquire ownership to land (in USh), adjusted for inflation					
Wave 1	480,707.80	1,457,172.00	0	17,991,005	723
Wave 2	863,434.30	1,989,108.00	0	22,869,023	606
Wave 3	543,346.50	1,551,339.00	0	20,000,000	505
Weather measures					
SPEI (current)	−0.31	1.09	−2.77	2.09	1834
SPEI (lag 1)	−0.70	0.94	−2.77	1.67	1834
SPEI (lag 2)	−0.17	0.89	−2.40	2.35	1834
SPEI (current): Dry	0.32	0.47	0	1	1834
SPEI (lag 1): Dry	0.42	0.49	0	1	1834
SPEI (lag 2): Dry	0.20	0.40	0	1	1834
SPEI (current): Wet	0.13	0.34	0	1	1834
SPEI (lag 1): Wet	0.05	0.21	0	1	1834
SPEI (lag 2): Wet	0.09	0.29	0	1	1834
SPEI (current): Normal	0.55	0.50	0	1	1834
SPEI (lag 1): Normal	0.53	0.50	0	1	1834
SPEI (lag 2): Normal	0.71	0.45	0	1	1834
Control variables					
Household size (in adult consumption equivalents)	4.39	1.96	0.77	15.47	1834
Total farm size (in hectar)	1.59	1.90	0.03	22.46	1834
Head has ever attended school	0.84	0.37	0	1	1834
Household received remittances in the past 12 months	0.32	0.47	0	1	1834
Average distance to parcels (in intervals of 15 min)	1.67	0.73	0.50	5.00	1834
Number of parcels with use rights	1.55	0.86	1	10	1834
Household consumption expenditures	160,857.40	132,198.30	9445.72	1,424,299.00	1834
Tropical livestock units	1.30	2.99	0	43.39	1834
Asset index	0.17	0.12	0	1	1834

Note: The weather measures and control variables are displayed as averages over time, using all three panel waves. Information is only presented for the sub-sample of households that hold use rights to land.

information on both precipitation and temperature, while the SPI relies only on precipitation. In addition, it is highly flexible, since it can be calculated for different time scales, capturing the temporal dimension of droughts, an advantage over the less flexible PDSI (Vicente-Serrano et al., 2010).

We spatially link the SPEI to household locations based on GPS coordinates. Temporally, we match the SPEI based on the main growing season for each location. The correct definition of the growing season is a point of vivid discussion in crop science. Correctly identifying the season is critical for the analysis of weather influences on crops, as the timing of precipitation and temperature conditions matters considerably for their effect (Rötter and Van de Geijn, 1999). The source we use for the growing season definition is the FAO crop calendar published for Uganda, which gives a fixed growing season for the main crops and distinguishes by rainy season regime (FAO, 2021). We calculate the SPEI values for each household location for the last month of the growing season. This captures drought conditions throughout the whole growing season and, thus, is most relevant for the agricultural setting. We provide further details on our approach in Appendix B.

For each wave, the SPEI was matched with the household survey data based on the month and year in which the interview took place, with the SPEI time point preceding the interview coded as the current value.[7] This leads to considerable differences in the time gap between the weather event and the interview, which ranges between a few days to just below 12 months, depending on the exact date of the interview. To account for this, we include fixed effects for the interview month in all specifications. Table 1 shows the SPEI for the main growing season in Uganda, as well as its first and second lags.

To facilitate interpretation of the SPEI, we additionally create categorical variables from the SPEI, with all values below −1 coded as "dry", values between −1 and +1 coded as "normal", and values above +1 coded as "wet". This follows conventional interpretation of the SPEI, where conditions above or below one standard deviation from the mean are generally considered weather anomalies (see Von Uexkull et al., 2016; Liu et al., 2021). SPEI values for Uganda exhibit considerable temporal variation, but also some spatial variation (Figs. 2 and C.1 in the Appendix).

5. Empirical strategy

Our identification strategy exploits exogenous spatial and temporal variation in drought conditions. We estimate the effects of drought during the growing season on households' willingness to purchase land as follows:

$$W_{it} = \beta_1 SPEI_{it} + \beta_2 SPEI_{it-1} + \beta_3 SPEI_{it-2} + \delta X_{it} + \alpha_i + \gamma_t + \theta_{it} + \epsilon_{it} \quad (1)$$

where W_{it} measures the willingness to acquire full ownership rights for at least one parcel the household currently has use rights for of household i surveyed in wave t. The coefficient β_1 measures the effect

[7] For example, if a household was interviewed in September 2009, the current growing season SPEI value assigned was SPEI-4 August 2009 for the unimodal area and SPEI-3 May 2009 for the bimodal area. However, a household interviewed in August 2009 was assigned the SPEI-4 August 2008 value as current growing season weather measure in the unimodal area, to ensure that the weather event always occurred before the interview.

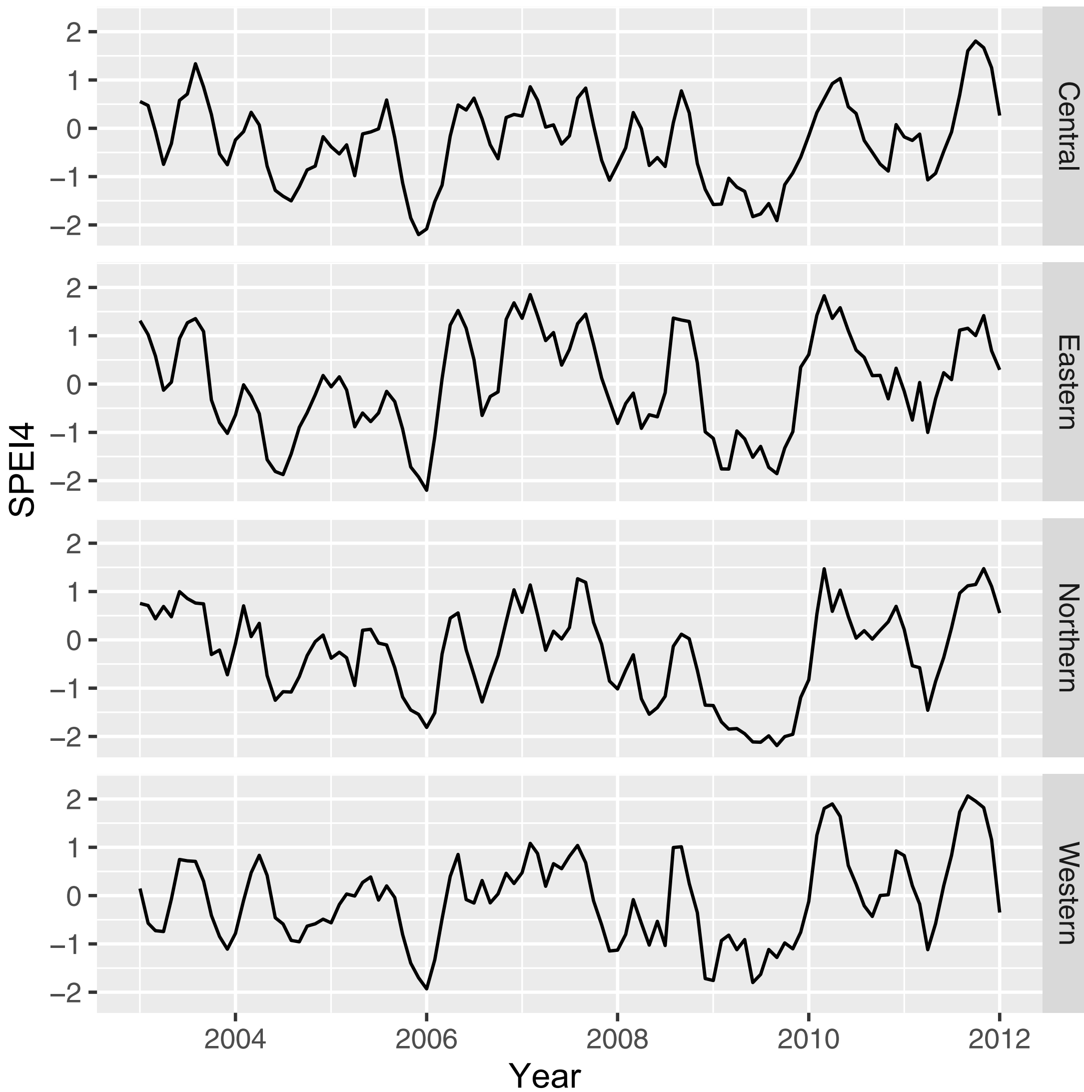

Fig. 2. Average monthly SPEI values with 4-month accumulation period in 2003–2012, by region.
Data source: CHIRPS for precipitation, and CHIRTS for temperature.

of the SPEI in the growing season preceding the interview, while β_2 and β_3 measure the effect of its first and second lag, respectively. Household fixed effects (α_i) account for time-invariant household characteristics, wave fixed effects (γ_t) capture common trends over time, and interview month fixed effects (θ_{it}) account for potential influences of the interview timing.[8] We apply attrition weights in all regressions to address potential bias stemming from panel attrition.

In our most parsimonious specification, we do not add control variables to avoid over-controlling. We then include X_{it}, a vector of time-varying household-level control variables, which is informed by the literature (e.g., Agarwal, 2003; Deininger et al., 2003; Rahman, 2010). It includes the number of adult equivalents and the total farm size held by the household (in hectare), which could both affect the household's willingness and financial ability to acquire land (Abebe et al., 2022; Flinn and Buttel, 1980). The education of the household head (measured with an indicator variable that takes the value one if the head has ever attended school) proxies knowledge and access to information (Galor et al., 2009). Another potential influence on land acquisition decisions is the receipt of remittances. At the same time, remittances are a potential channel that mediates effects of extreme weather on agricultural production (Generoso, 2015). We define an indicator variable taking the value one if a household received any remittances from within Uganda or abroad in the past 12 months. Land characteristics that could affect the relation between drought and the willingness to acquire ownership rights include the average distance of parcels from the homestead, as parcels further away may be more costly to farm and, hence, less attractive economically, as well as the number of parcels held by the household with use rights (Gonzalez et al., 2007). We further control for households' consumption expenditures, which serves as proxy for living standards.[9] Measures of wealth include livestock holdings, measured in tropical livestock units (Rothman-Ostrow et al., 2020), and an asset index derived from Principal Component Analysis. Overall, these household controls also reflect the adaptive capacity of the households. Most controls are potentially endogenous to the willingness to acquire land ownership. Thus, the coefficients estimated with controls should not be interpreted causally.

[8] We conducted a Hausman test, testing the null hypothesis that the random effects model is consistent, efficient, and preferable to the fixed effects model. The Hausman test yielded a test statistic of 49.54 with p<0.00, thus leading us to reject the null hypothesis.

[9] Following Appleton and Ssewanyana (2003), consumption expenditures were aggregated to a base period of 30 days and converted to 2005/06 prices (UBOS, 2011).

Table 2
Descriptive statistics by households' land ownership status.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	Owner-cum-users Mean	Owners Mean	p-value from t-test on equality of means
Household size (in adult consumption equivalents)	4.39	4.37	0.85
Household head is male	0.75	0.70	0.00***
Age of household head	43.60	48.86	0.00***
Head has ever attended school	0.84	0.76	0.00***
Household received remittances in the past 12 months	0.32	0.32	0.95
Household consumption expenditures	161,081.70	168,845.80	0.09*
Tropical livestock units	1.31	2.04	0.00***
Asset index	0.17	0.14	0.00***
Total farm size (in hectare)	1.60	2.04	0.00***
Number of parcels with use rights	3.05	2.06	0.00***
Average distance to parcels	1.66	0.90	0.00***
Region: Central	0.23	0.19	0.00***
Region: Eastern	0.31	0.26	0.00***
Region: Northern	0.22	0.31	0.00***
Region: Western	0.24	0.24	0.84
N	1878	2684	

Note: Column 3 reports results from unconditional t-tests on the equality of means, with *p < 0.10, **p < 0.05, ***p < 0.01. Means are calculated for the three waves combined.

Next, we estimate the effect of exposure to drought on the willingness to acquire land ownership at the intensive margin.

$$P_{it} = \beta_4 SPEI_{it} + \beta_5 SPEI_{it-1} + \beta_6 SPEI_{it-2} + \delta X_{it} + \alpha_i + \gamma_t + \theta_{it} + \epsilon_{it} \quad (2)$$

with P_{it} representing the price households report being willing to pay to acquire land ownership over parcels they currently have use rights for. The coefficients β_4, β_5, and β_6 again measure the effect of the current or lagged SPEI on the price outcome. The same set of controls, attrition weights, and fixed effects is used as in Eq. (1). Wave fixed effects (γ_t) also account for possible inflation effects to the extent that inflation was constant across regions.[10] P_{it} is a censored variable with zero as corner solution. Fig. C.2 in Appendix C shows its distribution, which is highly right-skewed. To account for this, we estimate Eq. (2) as a linear probability model with the outcome variable transformed with the inverse hyperbolic sine transformation, which has the advantage of retaining zero values. The linear probability model estimated with OLS can be a useful approach for estimating effects on the transformed outcome, but may lead to negative fitted values (Wooldridge, 2015). As a robustness test, we report results obtained from a Poisson fixed effects model in Section 6.4.

Since the effects of drought on the demand for purchasing land held with use rights may not occur immediately, we introduce lags of the SPEI into both models in a step-wise approach. The inclusion of lags of the weather variable has several advantages: it allows for studying the persistence of drought effects over time, while controlling for previous values of the weather variable leads to more precise estimates of contemporaneous shock impacts. Ignoring lagged effects may lead to misspecification bias. However, the calculation of standard errors needs to account for the serial correlation introduced by the lags into the model. We choose to cluster standard errors at the district level (with 98 districts covered by the survey) to account for survey design effects and events occurring at district level that might affect all households in the cluster.[11] When the number of cross-sectional units are substantially larger than the number of time periods, clustering also accounts for serial correlation (Wooldridge, 2015).

[10] Annual inflation rates during the survey years are 8.4% (2005), 13% (2009), and 4% (2010) (World Bank, 2022).

[11] Clustering at the level of the weather data (results available upon request) yields only minimally different results, with all main effects remaining significant.

6. Results and discussion

6.1. Differences between owners and owner-cum-users of land

Households with use rights to land and households who own all of their land differ in a number of ways.[12] Table 2 presents descriptive statistics for key demographic and land-related variables. Households that hold both use rights and ownership rights to land (owner-cum-users) have significantly younger and better educated heads and are more likely to be headed by a man compared to households that own all of their land. Owner-cum-user households have slightly lower consumption expenditures compared to owner households and own fewer livestock, but have higher asset endowments on average. Moreover, owner-cum-users have significantly smaller farms, but higher land fragmentation. On average, the parcels farmed by owner-cum-users are significantly further away from the homestead as compared to the parcels farmed by full owners. Geographically, significantly more owner-cum-users are located in the Central region and Eastern region compared to full owners.

6.2. Willingness to acquire ownership to land at the extensive margin

Results from an OLS estimation of Eq. (1) are displayed in Table 3, with the outcome variable being households' willingness to acquire full ownership rights for land currently held with use rights.[13] Panel A shows results obtained for the continuous SPEI measures. In the baseline model without time-varying household-level controls (col. 1), the coefficient estimate of the current SPEI is positive and statistically significant at the 5% level.[14] This indicates that exposure to drier conditions during the growing season preceding the survey interview lowers the demand for land ownership. Results are confirmed in col. 2, where the set of time-varying household-level controls is included. Next, we add the first lag of the SPEI, both in the model without household-level controls (col. 3) and with controls (col. 4). In both models, the estimated coefficients of both the current SPEI and the first

[12] All households in the sample own at least some land. Hence, there is no group of households only accessing land through use rights.

[13] We use a linear probability model, since probit or logit models with household fixed effects in panels that cover few time periods and many cross-sectional units suffer from the incidental parameter problem, leading to biased estimates.

[14] For comparability, we use the same sample in models with and without household-level controls. Using the maximum available sample for the baseline estimation yields almost identical results.

Table 3
Willingness to acquire full ownership rights for land currently held under use rights only.
Data sources: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Continuous SPEI measures						
SPEI (current)	0.06**	0.06**	0.08***	0.08***	0.09***	0.09***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
SPEI (lag 1)			0.08***	0.08***	0.08***	0.08***
			(0.03)	(0.02)	(0.03)	(0.02)
SPEI (lag 2)					0.05	0.05*
					(0.03)	(0.03)
R^2	0.65	0.66	0.66	0.67	0.66	0.67
Panel B: Categorical SPEI measures						
SPEI (current): Dry	−0.11	−0.11				
	(0.07)	(0.07)				
SPEI (lag 1): Dry	−0.14***	−0.15***				
	(0.05)	(0.05)				
SPEI (lag 2): Dry	−0.11*	−0.12*				
	(0.07)	(0.06)				
SPEI (current): Wet			0.14**	0.13**		
			(0.05)	(0.06)		
SPEI (lag 1): Wet			0.16	0.18*		
			(0.10)	(0.10)		
SPEI (lag 2): Wet			0.03	0.03		
			(0.06)	(0.07)		
SPEI (current): Normal					−0.01	−0.00
					(0.05)	(0.05)
SPEI (lag 1): Normal					0.09*	0.09*
					(0.05)	(0.05)
SPEI (lag 2): Normal					0.07	0.07
					(0.06)	(0.05)
R^2	0.65	0.66	0.65	0.66	0.65	0.66
Household controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1834	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

lag SPEI are positive and statistically significant at the 1% level. Adding the second lag of the SPEI (cols. 5 and 6) does not change the baseline results, while the estimated coefficient of the second lag of the SPEI is only significant at the 10% level in the model with household controls (col.6).

In panel B, we distinguish between different types of weather events and employ categorical variables that divide the SPEI in the categories “dry”, “normal”, and “wet” conditions. Results confirm the main findings from the continuous SPEI: Households exposed to drought conditions during the previous growing season are less likely to report they are willing to acquire full ownership rights for their land compared to households not exposed to drought (cols. 1 and 2). Interestingly, the negative effects of drought appear to persist over time: The second lag of the “dry” SPEI, indicating drought conditions in the growing season 2–3 years ago, still significantly lowers the demand for land ownership rights. In contrast, exposure to wet conditions in the previous growing season strongly and significantly increases the willingness of households to purchase land ownership rights (cols. 3 and 4). Yet, the effect of wet conditions on the demand for land ownership appears to be short-lived, as the first and second lag of the “wet” SPEI are not statistically significant at conventional levels, with the exception of the first lag when household controls are included.

As a refinement, we examine the spatial heterogeneity of effects across climatic zones. More specifically, we explore whether climatic conditions moderate the relationship between drought and the intention to acquire land ownership rights. To this end, we estimate the baseline model (Eq. (1)) separately for households living in areas that experience two rainy seasons per year (bimodal precipitation regime, prevalent in southern Uganda) and those living in areas with only one rainy season per year (unimodal precipitation regime, prevalent in Uganda’s northeast). Results, presented in Table C.1 in the Appendix, suggest that the effects of drought conditions on households’ willingness to acquire land ownership rights are particularly strong in areas with bimodal precipitation regimes (col. 1–3), which appear to drive the results obtained in the baseline model. This may possibly be explained by the type of crops grown in areas with bimodal precipitation regimes, which are less drought resilient on average than crops grown in unimodal regimes. For instance, in the Central region – Uganda’s breadbasket – farmers predominantly cultivate perennial crops, such as coffee and banana, which are not well-suited to tolerate shortages in precipitation. This makes the occurrence of drought conditions particularly detrimental in bimodal precipitation regimes.

6.3. *Willingness to acquire land ownership at the intensive margin*

Next, we analyze if drought has an effect on the amount households are willing to pay for acquiring ownership rights for land currently held with use rights. Results are displayed in Table 4, with the outcome being the inverse hyperbolic sine-transformed price households are willing to pay to obtain full ownership rights for their land. All models are estimated with OLS. Panel A shows results for the continuous SPEI. We find significant, positive, and large effects of the continuous SPEI on the amount households are willing to pay for land, indicating that drier conditions lower the demand for land ownership. The effects are of similar size in the baseline model without time-varying household-level controls (cols. 1, 3, and 5) and in the model that includes controls (cols. 2, 4, and 6). The estimated coefficients are positive and significant at least at the 10% level for both the current SPEI as well as its first and second lag.

In Panel B, we again transformed the SPEI into categories indicating “dry”, “normal”, and “wet” conditions. Households exposed to drought conditions report they are willing to pay a significantly lower price to obtain ownership rights than households exposed to normal or above average precipitation (cols. 1 and 2). Again, drought conditions during the two preceding growing seasons significantly reduce the amount households are willing to pay for secure land ownership rights. In contrast, exposure to wet conditions during the growing season preceding the survey interview increases the price households are willing to pay for purchasing land ownership rights. Overall, results are analogous to the results at the extensive margin presented above.

Results from the analyses at both the extensive and intensive margins suggest that drought persistently lowers the willingness of smallholder farmers to strengthen their land claims, with effects being detectable for up to three years. At the same time, above-average precipitation increases the demand for secure land ownership rights. This lends support to the hypothesis on land values, indicating that when households expect good prospects for agricultural production and, thus, income generation, obtaining full ownership rights to land is more attractive than in adverse weather conditions. Using the full-year SPEI instead of the growing season SPEI does not yield significant effects (Table C.2 in the Appendix). This suggests that the effect mainly works through the channel of agricultural production and income. The alternative hypothesis on potentially positive effects of drought on land acquisition intentions due to lower prices is not supported by our findings.

The overall positive coefficient of the continuous SPEI points to a preference for water availability above the mean, i.e. positive deviations from normal conditions. While this may seem counter-intuitive at first, because wet conditions in an extreme form can lead to water logging and damage crops, there are a number of reasons why wetter conditions may induce a positive response from farmers: First, the response function of yields to climatic conditions is not normally distributed over a dry-wet gradient. There is evidence for a response curve that is shifted somewhat to the right, favoring above-normal

Table 4
Amount households are willing to pay to acquire ownership rights to land.
Data sources: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Continuous SPEI measures						
SPEI (current)	0.83**	0.78**	1.07***	1.03***	1.19***	1.15***
	(0.35)	(0.35)	(0.33)	(0.34)	(0.34)	(0.35)
SPEI (lag 1)			1.01***	1.02***	1.03***	1.04***
			(0.38)	(0.36)	(0.37)	(0.36)
SPEI (lag 2)					0.79*	0.77*
					(0.44)	(0.41)
R^2	0.64	0.65	0.65	0.66	0.65	0.66
Panel B: Categorical SPEI measures						
SPEI (current): Dry	−1.57	−1.57				
	(0.99)	(0.99)				
SPEI (lag 1): Dry	−2.00***	−2.08***				
	(0.70)	(0.66)				
SPEI (lag 2): Dry	−1.61	−1.66*				
	(0.99)	(0.92)				
SPEI (current): Wet			1.83**	1.68**		
			(0.77)	(0.80)		
SPEI (lag 1): Wet			2.13	2.30		
			(1.49)	(1.56)		
SPEI (lag 2): Wet			0.73	0.72		
			(0.85)	(0.89)		
SPEI (current): Normal					−0.01	0.05
					(0.66)	(0.67)
SPEI (lag 1): Normal					1.26*	1.29*
					(0.71)	(0.68)
SPEI (lag 2): Normal					0.93	0.93
					(0.79)	(0.76)
R^2	0.65	0.66	0.64	0.65	0.64	0.65
Household controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1834	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The outcome is inverse hyperbolic sine transformed. Attrition weights applied.

precipitation over below-normal precipitation in rain-fed farming systems (Schierhorn et al., 2021). Second, the SPEI was calculated for the 1983–2016 baseline period and only gives information about deviation from the mean conditions, while it does not account for crop-specific water demand. Thus, wet conditions might still be beneficial for (certain) crops. By 2010, Uganda's climate had already warmed by ca. 1.3 °C since 1960, while precipitation decreased (McSweeney et al., 2010). With higher temperatures, the curve of optimal growing conditions for plants is shifted to the right: with more evapotranspiration, more water is needed. Third, land rented or sharecropped out by its owners is not always the most productive land, but rather marginal land that can be spared and where seasonal renters are used to bring it (back) into productive use. Such land may particularly benefit from wetter conditions, if the initial below-average state is linked to low soil moisture.

We explored potential heterogeneity in our results along three dimensions: (i) by poverty status, drawing on the poverty line calculated by Appleton et al. (2001) that applies the basic needs approach; (ii) by gender of the household head; and (iii) by farm size, using one hectare as threshold. Table C.3 in the Appendix displays results of models that include interaction terms between the continuous SPEI measure and poverty status (col. 1–2), gender of the head of household (col. 3–4), and farm size (col. 5–6). As in the baseline model, the estimated coefficients of the SPEI are significant in all but two models (col. 3–4). However, none of the interaction terms is statistically significant at conventional levels. Our conclusion from those results is that no heterogeneous effects of drought conditions on households' willingness to purchase land are detectable across poor and non-poor households, male and female-headed households, or households with small and large farm size. However, we do not conclude from those results that heterogeneity in drought impacts across those groups does not exist. Rather, the sample size of the analysis may be too small to yield detectable results.

6.4. Robustness tests

We perform a number of robustness tests to assess the credibility of the results. First, we calculate the SPEI for an alternative reference period (1983–2004), purposefully excluding recent years. Including recent years in the reference period can underestimate drought severity, at least in regions experiencing a drying trend (Um et al., 2017), which is the case in Eastern Africa (Haile et al., 2020). Results, presented in Table D.1 in the Appendix, are only marginally different in terms of effect size and statistical significance, indicating that results are not sensitive to the choice of the reference period.

Second, we calculate the SPEI for specific months in the growing season as an alternative measure of drought. In this case, we do not distinguish between households' location and precipitation regimes for temporal matching. This approach allows assessing which months are important in aggregate. Results (Table D.2 in the Appendix) show strong effects of drought conditions on the willingness to acquire ownership rights for land that are roughly comparable with the baseline model in terms of magnitude and significance levels.

Third, we include the third lag of the SPEI in all models to test if effects persist beyond three years. The inclusion of a further lag is not individually statistically significant at conventional levels, while estimates for the current SPEI, first lagged SPEI, and second lagged SPEI remain similar (Table D.3). In addition, we show results of a placebo test, in which the willingness to acquire land ownership was regressed on the lead SPEI. As expected, the estimated coefficient of the lead SPEI is not statistically significant at conventional levels and negligible in size.

Fourth, we explore whether results are driven by the Mailo system in Uganda, which is known for its overlapping land rights with complex land use and land ownership. Only a small part of our sample households (about 6%) fall under Mailo tenure, which we exclude from the estimations in this robustness test. Results (Table D.4) for both outcomes are roughly comparable to the ones obtained in the baseline specification.

Fifth, to explore the robustness of results to the model choice, we use a non-linear model – a probit maximum likelihood estimator – to estimate Eq. (1). To account for the incidental parameter problem that occurs in probit models with many fixed effects, we apply a bias correction developed by Fernández-Val and Weidner (2016). Results, displayed in Table D.5 in the Appendix, show similar signs of the estimated coefficients of the SPEI measures and comparable significance levels as those obtained with linear probability models. Note that the size of the estimated coefficients is not directly comparable across linear probability models (baseline) and probit models, as the coefficients estimated with probit show an increase in the probability attributed to a one-unit increase in a given predictor. In addition, all observations with constant outcomes over time are dropped from the estimation, which lowers the effective sample size.

Sixth, we estimate Eq. (2) with a Poisson quasi-maximum likelihood estimator to take into account the censored nature of the second outcome variable, the price households are willing to pay for land (Table D.6). Poisson fixed effects models are better suited than OLS if the outcome variable is censored (Wooldridge, 1999), but have the disadvantage of dropping all observations for which the outcome is always zero. Results show the same signs as in the OLS estimation, while the estimated coefficients are smaller in magnitude, since the estimates represent the expected change in logs.[15]

Seventh, to further test whether alternative models confirm our results, we estimate Eqs. (1) and (2) using a correlated random effects (CRE) model (Table D.7 in the Appendix). Eq. (1) is estimated with CRE probit to account for the binary nature of the dependent variable, whereas Eq. (2) is estimated as CRE tobit model, since the outcome variable is censored. The CRE approach combines elements of random and fixed effects estimators. It specifically models the *within* and the *between* variation in time-varying predictors and, instead of using household fixed effects, explicitly includes time-invariant control variables. The models estimated with CRE contain fewer observations compared to the main specification, since some time-invariant control variables have missing values. The results confirm our results from the baseline specifications and from Tables D.5 and D.6. While the coefficient estimates are not directly comparable, the signs and significance levels of the *within* estimates are similar to the estimated coefficients of the baseline model in most cases.

Finally, results presented so far focused on the short-term effects of drought conditions. To explore whether effects also hold in the medium term, we now calculate the average SPEI for a 3-year and 5-year period. Analyzing the effects of average SPEI values over several years reveals the aggregate impact of recurring dry conditions on land purchase interests. Results at the extensive margin are displayed in Table D.8 in the Appendix, while results on the intensive margin are presented in Table D.9. Results show that the aggregate effect is highly significant for both outcomes, and for both the 3-year and 5-year SPEI. We take this as supporting evidence of the findings obtained in our baseline analysis, where the annual SPEI is employed to measure drought occurrences.

7. Conclusion

In this study, we examine the effects of exposure to drought on the willingness of smallholder farmers in Uganda to purchase land and the price they are willing to pay for it. Our study is the first to quantify the effects of drought on households' intention to purchase land. Our analysis builds on detailed household panel survey data with three waves that we combine with high-resolution weather data to calculate the SPEI drought index. Using a household fixed effects model, we exploit variation in drought intensity across time and space.

We document that exposure to drought reduces both the willingness of households to acquire land ownership rights and the price households are willing to pay for such rights. The effects are persistent over time, up until two years after a drought occurs. In contrast, exposure to above-average water supply increases households' interest to purchase land ownership rights. Both results hold in the medium term, with large aggregate effects of drought conditions on households' willingness to purchase land.

Those results offer insights for land use policies and policies aimed to improve household resilience in the face of drought. Regions affected by frequent droughts are less attractive for land purchases, which may also undermine farmers' investment in such land. Targeted efforts to improve land suitability for crop production in the face of drought are needed, for instance in the form of integrated soil management or irrigation systems, while particular attention to drought-prone areas in adaptation and disaster risk reduction planning is warranted.

Our analyses are subject to limitations. First, the SPEI is calculated on a monthly basis and accumulates water balance conditions, which makes it unable to detect potentially detrimental effects of drought at different phases of plant growth within a season. However, crop responses to drought are likely to take longer to manifest and extremes have a legacy effect on soils. Second, the SPEI captures conditions in a given location relative to its baseline value, thus the interpretation is not straightforward as dry or wet conditions mean different things depending on context, even if expressed in relative terms.

Our focus in this study is exclusively on how drought influences the intentions of farmers to purchase land they cultivate with use rights. Future research may investigate in more general terms the way in which climatic conditions and extreme weather shape farmers' relation with their land and the rules of its access and control. In particular, potential effects of longer-term changes in climatic conditions on land purchase, tenure regimes, and perceived tenure security should be studied to better understand how farmers respond to climatic changes with their agricultural production-, risk-coping, and potential relocation decisions.

CRediT authorship contribution statement

Lisa Murken: Conceptualization, Data curation, Formal analysis, Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. **Kati Kraehnert:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **Christoph Gornott:** Funding acquisition, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Attrition analysis

See Tables A.1–A.3.

Appendix B. Identifying the growing season

Approaches for defining the growing season can be based on (1) simple cut-off observations from fields for the specific country or region; (2) satellite observations, such as from Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI); and (3) climatological definitions based on rainy season onset and cessation and/or temperature. In the context of our study, applying a precise definition is challenging due to the heterogeneity in cropping patterns in the household sample. The average (median) farmer in our sample cultivates 6.3 (6.0) different crops in the main growing season, making the use of detailed phenological and climatological knowledge on the growing season difficult. This is further complicated by Uganda's precipitation regimes: As Uganda exhibits two growing seasons in most parts of the country, but only one growing season in the north with a

[15] To handle the many zero values, a zero-inflated Poisson regression model would be more appropriate, but we are not aware of an estimation method for such models that can handle household fixed effects.

Table A.1
Unconditional t-tests on the equality of means between attrited households and households that remained in the panel.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11).

Statistic	Household attrited from the panel Mean	Household remained in the panel Mean	*p*-value from t-test on equality of means
Willingness to acquire full ownership rights for land conditional on having use rights	0.37	0.38	0.85
Amount households are willing to pay to acquire ownership to land	794,106.3	319,696.4	0.18
N	403	1543	

Note: Column 3 reports results from unconditional t-tests on the equality of means, with *p < 0.10, **p < 0.05, ***p < 0.01.

Table A.2
Determinants of staying in the panel survey over time.
Data sources: UNPS (waves 2005/06, 2009/10, and 2010/11).

Dependent variable: Household was surveyed in all three waves	All households (1)	Owner-cum-users (2)
Household size (in adult consumption equivalents)	0.01	0.00
	(0.00)	(0.01)
Total farm size (in hectare)	0.00	0.00
	(0.00)	(0.01)
Head attended school in the past	0.01	0.02
	(0.02)	(0.03)
Household received remittances in the past 12 months	−0.02	0.00
	(0.02)	(0.02)
Average distance (in intervals of 15 min)	−0.01	−0.01
	(0.01)	(0.01)
Household head is male	−0.02	0.02
	(0.02)	(0.03)
Household consumption expenditures	−0.00*	−0.00
	(0.00)	(0.00)
Tropical livestock units	0.00	−0.00
	(0.00)	(0.00)
Asset index	0.06	0.14
	(0.08)	(0.11)
Willingness to acquire full ownership rights to land conditional on having use rights		0.00
		(0.02)
Amount households are willing to pay to acquire ownership to land		−0.00**
		(0.00)
Number of parcels with use rights		0.03**
		(0.01)
Pseudo R^2	0.05	0.55
N	1711	811

Note: Estimated with probit. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Coefficients show average marginal effects. All control variables are constructed from wave 1 data.

Table A.3
Comparing mean values of key household characteristics in UNPS wave 3 (2010/11) and wave 8 (2019/20).
Data source: UNPS (waves 2010/11 and 2019/20).

	Wave 3 (2010/11)	Wave 8 (2019/20)	*p*-value from t-test on equality of means
Panel A: Full sample			
Share of owner-cum-users	0.36	0.35	0.34
N	1859	2208	
Panel B: Owner-cum-user sample			
Share of farmland that is accessed with use rights	0.50	0.58	0.00***
Total farm size (in hectare)	1.38	1.15	0.01**
Household size (in adult consumption equivalents)	4.17	4.01	0.10
Household head is male	0.74	0.67	0.00***
Age of household head	43.85	44.94	0.14
Head has ever attended school	0.86	0.91	0.02**
Household received remittances in the past 12 months	0.25	0.35	0.00***
N	671	764	

Column 3 reports results from unconditional t-tests on the equality of means, with *p < 0.10, **p < 0.05, ***p < 0.01.

Table B.1
Dominant crops grown in Uganda, by region.
Data sources: UNPS (waves 2005/06, 2009/10, and 2010/11) and the 2008/2009 Uganda Census of Agriculture (UBOS, 2010).

Region	Crop	Number of households reporting as highest yielding	UBOS Production [Metric tons] (2008/09)	UBOS Acreage [ha] (2008/09)
Central	Banana	407	929,534	283,472
Eastern	Maize	424	1,108,554	388,762
Northern	Cassava	384	983,124	269,886
Western	Banana	785	2,728,587	458,312

Fig. B.1. Map of Uganda with the four regions of Uganda and main water bodies.

Table C.1
Heterogeneous effects of SPEI on the willingness to acquire ownership rights by precipitation regime.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	Bimodal precipitation regime			Unimodal precipitation regime		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (current)	0.07***	0.09***		−0.00	0.00	
	(0.03)	(0.03)		(0.09)	(0.09)	
SPEI (lag 1)		0.08**			0.09	
		(0.03)			(0.06)	
SPEI (lag 2)		0.06*			0.05	
		(0.04)			(0.06)	
SPEI (current): Dry			−0.11			−0.06
			(0.08)			(0.23)
SPEI (lag 1): Dry			−0.14**			−0.03
			(0.05)			(0.11)
SPEI (lag 2): Dry			−0.13*			−0.00
			(0.07)			(0.14)
Household controls	No	No	No	No	No	No
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.63	0.64	0.63	0.73	0.73	0.73
N	1420	1420	1420	414	414	414

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

transitional zone in between, the exact definition of the growing season for each household location is challenging.

Other studies that match weather data to agricultural data have commonly employed gridded crop calendars and matched the growing season based on the dominant crop of the respective grid cell. One such crop calendar is the MIRCA crop calendar (Portmann et al., 2010), which contains information on the growing season of major crops globally. However, it is criticized and found to be unreliable in local studies with high resolution (Kim et al., 2021).

The correct identification of the growing season is further complicated by shifts in seasonal precipitation patterns affected by climate change. The rains sometimes extend into the dry season and dry spells plague the former rainy season, making correct prediction of the rainy season and growing season increasingly difficult. In Uganda, a study found that the probability of a location to experience a false start of the growing season is between 0 and 53% (Ocen et al., 2021).

Given the described difficulties, we employ a rather simple approach to defining the growing season for each household location and test several alternative approaches. With regard to the rainy season, which is critical for the crop growing season, one study finds that more complex climatological definitions offer little additional accuracy over simpler definitions based on (sub-)national knowledge of the rainy season timing (Seregina et al., 2019).

We consulted different sources of information on the growing seasons in Uganda, including from the Ugandan Ministry of Agriculture, Animal Industry and Fisheries (MAAIF), FEWS Net, the US Department of Agriculture, newspaper articles, and journal articles. Since no

Table C.2
Full-year SPEI for the month before the survey interview.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land		Amount households are willing to pay	
	(1)	(2)	(3)	(4)
SPEI12 (current)	0.01	0.02	0.17	0.35
	(0.03)	(0.03)	(0.42)	(0.47)
SPEI12 (lag 1)		0.02		0.37
		(0.04)		(0.51)
SPEI12 (lag 2)		0.03		0.44
		(0.03)		(0.51)
Household controls	No	No	No	No
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R^2	0.64	0.64	0.64	0.64
N	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

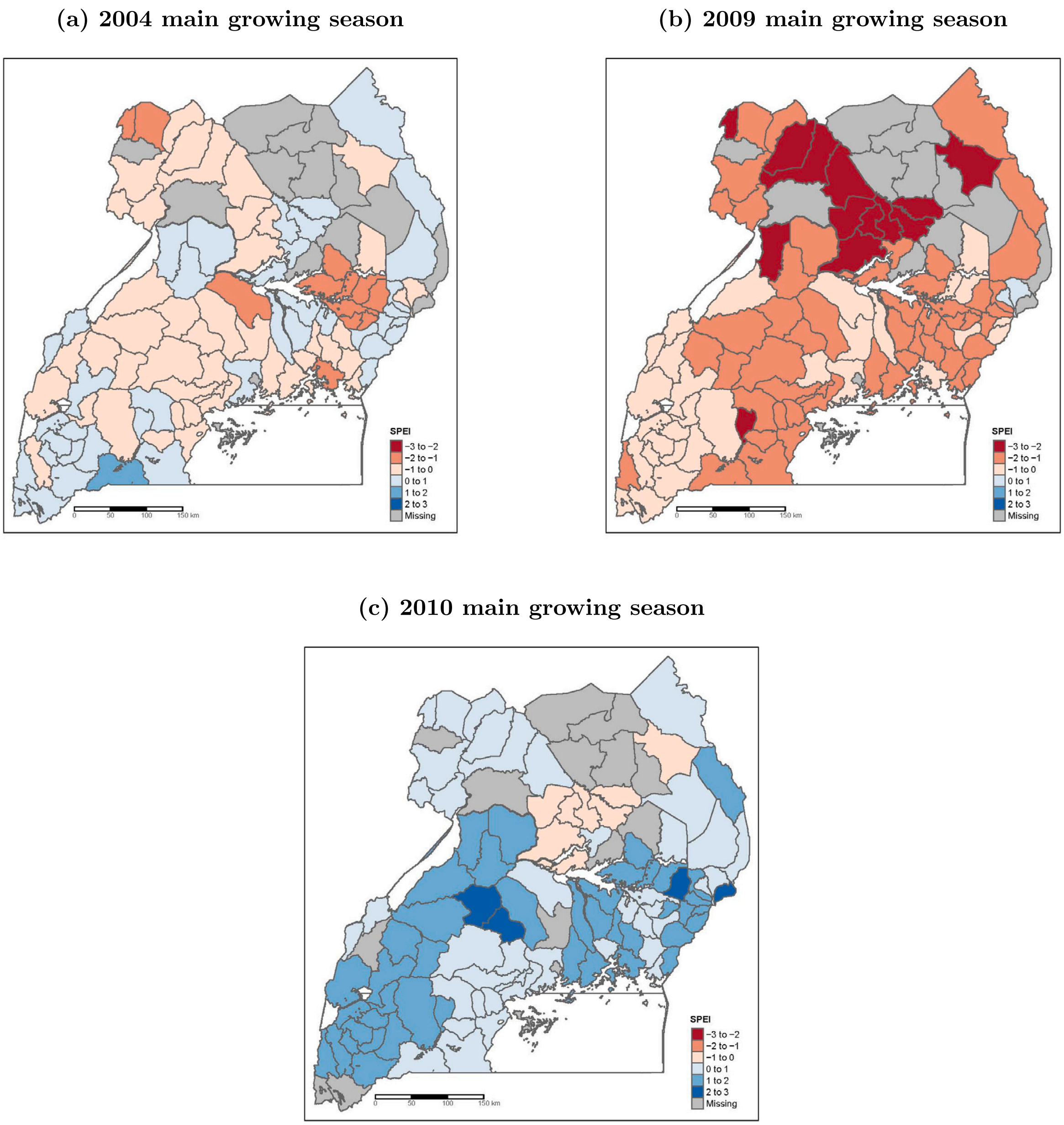

Fig. C.1. SPEI with 4-month accumulation period for selected years, by district.
Data source: CHIRPS for precipitation and CHIRTS for temperature.

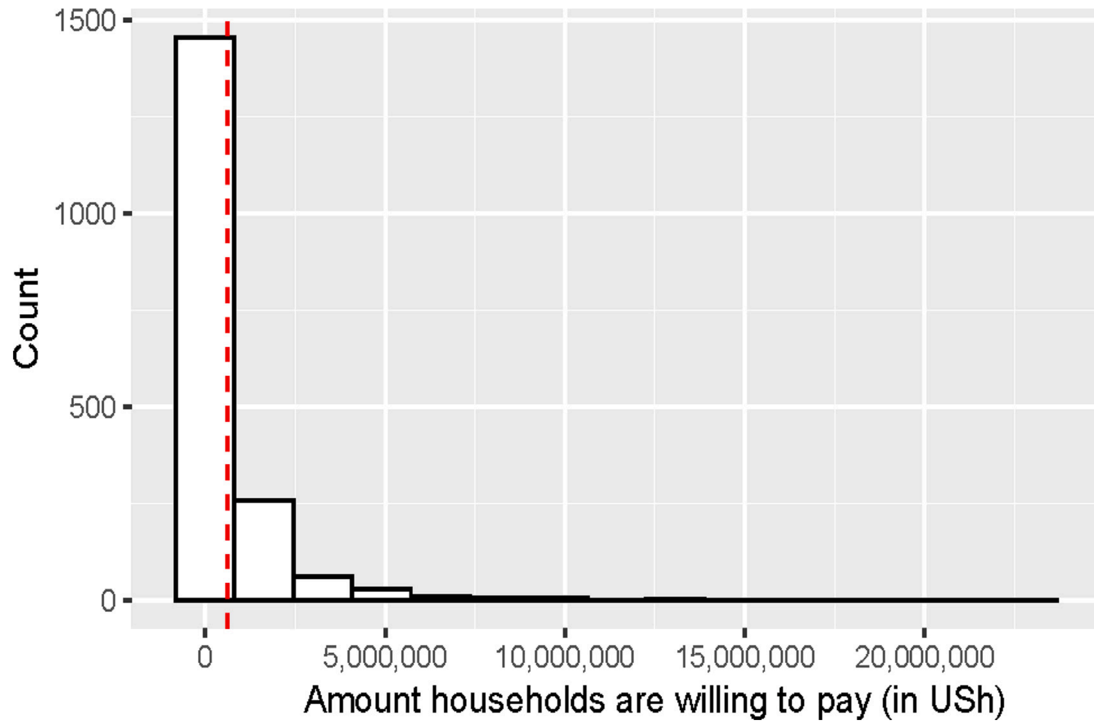

Fig. C.2. Distribution of the amount households are willing to pay to acquire parcels (in Uganda Shillings). *Data source:* UNPS (waves 2005/06, 2009/10, and 2010/11). The red line shows the mean. In 2010, 1 Euro was worth about 2750 Uganda Shillings. The variable is adjusted for inflation using the Consumer Price Index (CPI), with 2010 defined as the base year.

Table C.3
Heterogeneous effects of SPEI on the willingness to acquire land ownership rights by poverty status, gender of head of household and farm size. *Data source:* UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to acquire land ownership rights					
	By poverty status		By gender of head		By farm size	
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (current)	0.08**	0.07**	0.05	0.05	0.06*	0.05*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Household is poor	−0.07	−0.03				
	(0.05)	(0.05)				
SPEI (current) ∗ household is poor	−0.03	−0.04				
	(0.04)	(0.04)				
Household head is male			0.22*	0.22*		
			(0.13)	(0.12)		
SPEI (current) ∗ household head is male			0.02	0.01		
			(0.04)	(0.04)		
Farm is small					−0.06	−0.03
					(0.06)	(0.06)
SPEI (current) ∗ farm is small					0.01	0.01
					(0.03)	(0.03)
Household controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.65	0.66	0.65	0.66	0.65	0.66
N	1804	1804	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied. “Household is poor” is an indicator variable that takes the value one if the household falls below the poverty line. “Farm is small” is an indicator variable that takes the value one if the household owns less than one hectare of farmland.

Table D.1
Robustness test - SPEI reference period from 1983–2004.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land				Amount households are willing to pay			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI (current)	0.06**	0.05**	0.09***	0.09***	0.75**	0.73**	1.18***	1.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.32)	(0.32)	(0.33)	(0.33)
SPEI (lag 1)			0.08***	0.08***			1.05***	1.06***
			(0.02)	(0.02)			(0.36)	(0.35)
SPEI (lag 2)			0.05*	0.05*			0.78*	0.76**
			(0.03)	(0.03)			(0.42)	(0.39)
Household controls	No	Yes	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.65	0.66	0.66	0.67	0.64	0.65	0.66	0.67
N	1834	1834	1834	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

two sources completely agree, we use the crop calendar published by the FAO (2021) for Uganda, which is widely used in the literature.

We base our definition of the growing season for the SPEI on the crop calendar by FAO (2021), information on the rainy seasons provided by FEWS Net (2022), and information included in the household survey on whether households experience one or two rainy seasons. We focus on the main growing season in each region, which in the bimodal areas corresponds to the first growing season, which is longer and generally considered to be the main growing season. The main growing season in the north extends from May to August for the main staple crops maize, millet, sweet potato, and cassava. In the south, the main growing season for the staples maize, millet, and beans ranges from March to May. The accumulation period is chosen to cover all months of the growing season up until the respective end month. For the end month of the growing season, the last month defined by FAO as "growing" is chosen.

Accordingly, we match SPEI values for the end of the growing season as follows: For the bimodal areas, the SPEI 3 in May is defined as the SPEI value for the growing season, in the unimodal areas, the SPEI 4 in August is chosen. The number indicates the number of months over which the SPEI is accumulated.

To analyze agricultural droughts, SPEI accumulation periods between 3–6 months are usually used, whereas for hydrological droughts longer timeframes are considered (Bachmair et al., 2016; Li et al., 2015). Since drought conditions can vary locally, we calculate the SPEI at high spatial resolution, using the R package "SPEI" developed by the Climatology and Climate Services Research Center.[16]

As an alternative solution for defining the relevant growing season for each location, we assign SPEI values based on the dominant crop in each of the four regions of Uganda and their respective growing seasons. Fig. B.1 shows the four regions of Uganda. The main crops grown per region are drawn from the household survey. We count the number of households that report a specific crop as their highest yielding crop (in absolute terms). Table B.1 shows the dominant crops from the survey. The aggregate number of dominant crops per region aligns with the figures from the 2008/09 Uganda Census of Agriculture conducted by the Uganda Bureau of Statistics (UBOS, 2010). In the Northern region, the highest yielding crop is cassava, in the Eastern region it is maize, followed by sweet potatoes. For the Central region and Western region, banana gives the highest yields (mainly cooking banana, but sweet banana and banana for beer production is also grown). The resulting matching gives similar results to our preferred approach.

[16] Different options exist for calculating potential evapotranspiration; we use the Hargreaves method, which balances input data needs with accuracy.

Table D.2
Robustness test - monthly SPEI.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land				
	(1)	(2)	(3)	(4)	(5)
SPEI3-May (current)	0.07***				
	(0.02)				
SPEI3-May (lag 1)	0.04				
	(0.03)				
SPEI3-May (lag2)	0.05				
	(0.03)				
SPEI4-June (current)		0.09***			
		(0.03)			
SPEI4-June (lag 1)		0.05			
		(0.03)			
SPEI4-June (lag2)		0.04			
		(0.03)			
SPEI5-July (current)			0.10**		
			(0.04)		
SPEI5-July (lag 1)			0.08**		
			(0.03)		
SPEI5-July (lag 2)			0.01		
			(0.03)		
SPEI5-August (current)				0.09**	
				(0.04)	
SPEI5-August (lag 1)				0.05	
				(0.03)	
SPEI5-August (lag 2)				0.03	
				(0.03)	
SPEI6-September (current)					0.10**
					(0.04)
SPEI6-September (lag 1)					0.05*
					(0.03)
SPEI6-September (lag 2)					0.06**
					(0.03)
Household controls	No	No	No	No	No
Household FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.65	0.65	0.65	0.65	0.66
N	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

Appendix C. Additional tables and figures

See Figs. C.1 and C.2. See Tables C.1–C.3.

Appendix D. Robustness

See Tables D.1–D.9

Table D.3
Robustness test - inclusion of third lag of SPEI and lead SPEI.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land		Amount households are willing to pay	
	(1)	(2)	(3)	(4)
SPEI (current)	0.09***		1.18***	
	(0.03)		(0.34)	
SPEI (lag 1)	0.08***		1.08***	
	(0.03)		(0.40)	
SPEI (lag 2)	0.05		0.82*	
	(0.03)		(0.47)	
SPEI (lag 3)	0.01		0.19	
	(0.02)		(0.33)	
SPEI (lead)		0.00		0.06
		(0.02)		(0.28)
Household controls	No	No	No	No
Household FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R^2	0.66	0.64	0.65	0.64
N	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

Table D.4
Robustness test - exclusion of Mailo land.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable	Willingness to purchase land			Amount households are willing to pay		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (current)	0.06**	0.09***		0.85***	1.22***	
	(0.03)	(0.03)		(0.36)	(0.36)	
SPEI (lag 1)		0.08***			1.08***	
		(0.03)			(0.39)	
SPEI (lag 2)		0.04			0.72	
		(0.03)			(0.50)	
SPEI (current): Dry			−0.13*			−1.77*
			(0.07)			(1.06)
SPEI (lag 1): Dry			−0.16***			−2.21***
			(0.05)			(0.75)
SPEI (lag 2): Dry			−0.11			−1.61
			(0.08)			(1.13)
Household controls	No	No	No	No	No	No
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.66	0.67	0.67	0.65	0.67	0.66
N	1720	1720	1720	1720	1720	1720

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

Table D.5
Robustness test - Probit model with bias correction for fixed effects.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Continuous SPEI measures						
SPEI (current)	0.21**	0.19*	0.24***	0.22**	0.28***	0.26***
	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)	(0.10)
SPEI (lag 1)			0.24**	0.25**	0.25***	0.25***
			(0.10)	(0.10)	(0.10)	(0.10)
SPEI (lag 2)					0.21*	0.20
					(0.12)	(0.12)
Pseudo R^2	0.13	0.15	0.16	0.18	0.17	0.20
Panel B: Categorical SPEI measures						
SPEI (current): Dry	−0.39	−0.40				
	(0.27)	(0.27)				
SPEI (lag 1): Dry	−0.51***	−0.51***				
	(0.19)	(0.19)				
SPEI (lag 2): Dry	−0.42	−0.43*				
	(0.26)	(0.26)				
SPEI (current): Wet			0.51***	0.44**		
			(0.20)	(0.20)		
SPEI (lag 1): Wet			0.66*	0.70*		
			(0.37)	(0.37)		
SPEI (lag 2): Wet			0.10	0.08		
			(0.26)	(0.28)		
SPEI (current): Normal					−0.04	−0.00
					(0.17)	(0.18)
SPEI (lag 1): Normal					0.32	0.33
					(0.20)	(0.20)
SPEI (lag 2): Normal					0.27	0.28
					(0.23)	(0.23)
Pseudo R^2	0.15	0.17	0.13	0.15	0.12	0.15
Household controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	730	730	730	730	730	730

(*continued on next page*)

Table D.5 (*continued*).

Probit models estimated with maximum likelihood. Coefficients show the increase in probability attributed to a one-unit increase in a given predictor, bias corrected following Fernández-Val and Weidner (2016). Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Observations with constant outcomes over time are dropped from the estimation.

Table D.6
Robustness test - Poisson.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Amount households are willing to pay				
	(1)	(2)	(3)	(4)	(5)
SPEI (current)	0.19***	0.18***			
	(0.07)	(0.07)			
SPEI (lag 1)	0.19***	0.20***			
	(0.07)	(0.07)			
SPEI (lag 2)	0.17**	0.17**			
	(0.08)	(0.08)			
SPEI (current): Dry			−0.22		
			(0.17)		
SPEI (lag 1): Dry			−0.35***		
			(0.12)		
SPEI (lag 2): Dry			−0.31*		
			(0.17)		
SPEI (current): Wet				0.34**	
				(0.14)	
SPEI (lag 1): Wet				0.56**	
				(0.25)	
SPEI (lag 2): Wet				0.16	
				(0.14)	
SPEI (current): Normal					−0.02
					(0.11)
SPEI (lag 1): Normal					0.23*
					(0.12)
SPEI (lag 2): Normal					0.18
					(0.13)
Household controls	No	Yes	No	No	No
Household FE	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.10	0.11	0.09	0.09	0.09
N	1123	1123	1123	1123	1123

Note: All models are estimated with Poisson quasi-maximum likelihood. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. The outcome is inverse hyperbolic sine transformed. Observations with constant outcomes over time are dropped from the estimation.

Table D.7
Robustness test – Probit and tobit correlated random effects models.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land				Amount households are willing to pay			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI (current) – within	0.10**				0.89*			
	(0.05)				(0.49)			
SPEI (current) – between	−0.01				0.09			
	(0.06)				(0.69)			
SPEI (lag 1) – within	0.22***				2.22***			
	(0.05)				(0.52)			
SPEI (lag 1) – between	0.02				0.76			
	(0.07)				(0.72)			
SPEI (lag 2) – within	0.26***				2.93***			
	(0.06)				(0.65)			
SPEI (lag 2) – between	−0.10				−1.06			
	(0.07)				(0.79)			
SPEI (current): Dry – within		−0.05				−0.07		
		(0.11)				(1.12)		
SPEI (current): Dry – between		−0.02				−0.30		
		(0.13)				(1.48)		
SPEI (lag 1): Dry – within		−0.48***				−4.89***		
		(0.11)				(1.11)		
SPEI (lag 1): Dry – between		−0.02				−1.13		
		(0.12)				(1.28)		
SPEI (lag 2): Dry – within		−0.55***				−5.78***		
		(0.13)				(1.28)		
SPEI (lag 2): Dry – between		0.11				0.84		
		(0.14)				(1.57)		
SPEI (current): Wet – within			0.14				1.08	
			(0.15)				(1.51)	
SPEI (current): Wet – between			−0.02				−0.17	
			(0.16)				(1.87)	
SPEI (lag 1): Wet – within			0.14				1.20	
			(0.23)				(2.45)	
SPEI (lag 1): Wet – between			0.02				2.01	
			(0.27)				(3.15)	
SPEI (lag 2): Wet – within			0.35**				4.06**	
			(0.17)				(1.78)	
SPEI (lag 2): Wet – between			−0.05				−0.85	
			(0.19)				(2.23)	
SPEI (current): Normal – within				−0.10				−1.09
				(0.10)				(1.03)
SPEI (current): Normal – between				0.06				0.42
				(0.13)				(1.45)
SPEI (lag 1): Normal – within				0.39***				4.26***
				(0.11)				(1.11)
SPEI (lag 1): Normal – between				0.03				0.82
				(0.12)				(1.31)
SPEI (lag 2): Normal – within				0.33***				3.53***
				(0.11)				(1.10)
SPEI (lag 2): Normal – between				−0.08				−0.48
				(0.13)				(1.44)
Time-variant household controls	No	No	No	No	No	No	No	No
Time-invariant household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2167.37	2169.06	2201.21	2180.06	6786.25	6786.94	6822.59	6799.32
N	1671	1671	1671	1671	1671	1671	1671	1671

Note: Models 1–4 are estimated with probit maximum likelihood, models 5-8 are estimated with tobit maximum likelihood. Standard errors in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01.

Table D.8
Robustness test - Effect of long-term SPEI on the willingness to acquire ownership rights.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Willingness to purchase land							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI - 5-year average	0.21***	0.21***						
	(0.08)	(0.08)						
SPEI - 3-year average			0.22***	0.22***				
			(0.06)	(0.06)				
SPEI: dry - 5-year average					−0.33*	−0.36*		
					(0.19)	(0.18)		
SPEI: dry - 3-year average							−0.37***	−0.38***
							(0.13)	(0.12)
Household controls	No	Yes	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.65	0.66	0.66	0.67	0.64	0.65	0.65	0.66
N	1834	1834	1834	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

Table D.9
Robustness test - Effect of long-term SPEI on the price the household would pay for purchasing land.
Data source: UNPS (waves 2005/06, 2009/10, and 2010/11), CHIRPS for precipitation, and CHIRTS for temperature.

Dependent variable:	Amount households are willing to pay							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI - 5-year average	3.04***	2.98***						
	(1.08)	(1.07)						
SPEI - 3-year average			3.02***	2.99***				
			(0.89)	(0.85)				
SPEI: dry - 5-year average					−4.38	−4.83*		
					(2.70)	(2.62)		
SPEI: dry - 3-year average							−5.25***	−5.39***
							(1.84)	(1.73)
Household controls	No	Yes	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.64	0.65	0.65	0.66	0.64	0.65	0.65	0.66
N	1834	1834	1834	1834	1834	1834	1834	1834

Note: Estimated with OLS. Standard errors, clustered at the district level, in parentheses with *p < 0.10, **p < 0.05, ***p < 0.01. Attrition weights applied.

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