Household climate adaptations reflect patterning in climate events

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Abstract

It is well-documented that households respond to climate events with climate adaptations, risk-management strategies like livelihood diversification, migration, or remittances – sending money and goods across distances. However, the focus is largely on responses to single climate events, while suggestive evidence indicates that temporal and spatial patterns across multiple events – including event frequency, clustering, and spatial extent – predict which climate adaptations households use. Here, we assess whether households that have experienced not just more severe droughts, but more frequent, temporally autocorrelated, or spatially extensive droughts across recent years, are more likely to have received a remittance over the last 12 months. We analyze remittance data from 2009 from 11,776 households across six sub-Saharan African countries, matching it to satellite and weather station data on precipitation and evapotranspiration (1981-2009). We find that average severity and average spatial extent of drought over a five-year window predict receiving a remittance; these effects are largely driven by remittances from household migrants, especially those who moved more than five years ago. In short, to predict what adaptations households will use in the face of climate events like drought, researchers should consider not just single events, but patterning across events; doing so will help us better anticipate and support adaptations like remittances given future climate projections.

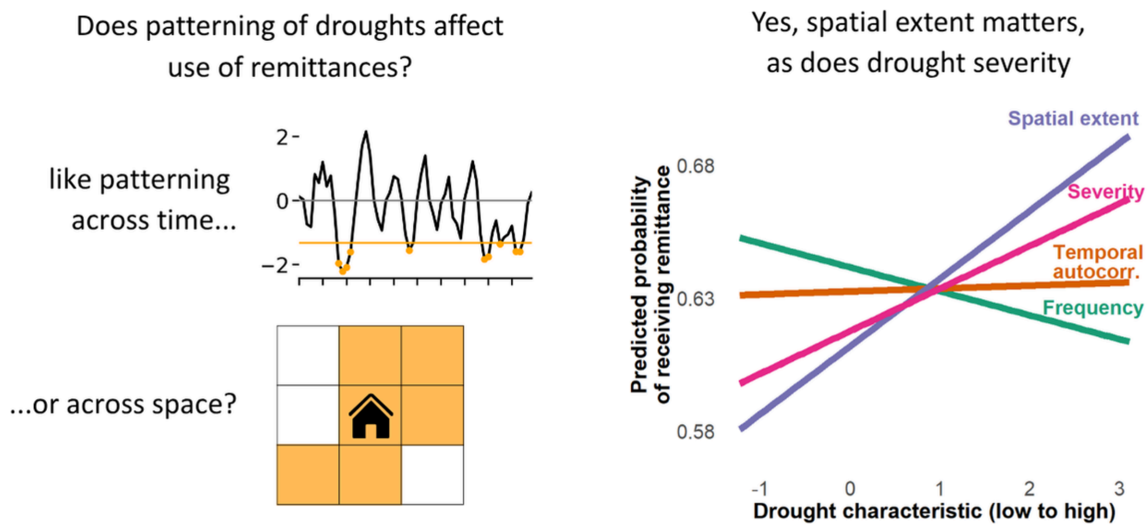
Keywords

climate adaptation, remittances, migration, drought, sub-Saharan Africa

Highlights

- Patterning in droughts across space and time likely impacts household decision-making
- Here, in most models, average severity and average spatial extent predict remittances
- Household migrants who moved more than five years ago are especially responsive
- Researchers should focus more on patterning when studying household climate adaptation

Graphical abstract



1. Introduction

When climate events impact livelihoods, households respond by diversifying their income sources, receiving money or goods from elsewhere, or even migrating temporarily or permanently (Agrawal, 2010; Halstead & O'Shea, 1989; Pisor et al., 2023; Thornton & Manasfi, 2011). Sometimes households prepare in advance for future events, and are more likely to do so if they have experienced events before and believe they can effectively prepare (Van Valkengoed & Steg, 2019). Reducing the risks of climate impacts through preparation or response is called climate-change adaptation. We know that a severe climate event can increase the probability of household response, whether the event was recent or even in the last decade (e.g., Gallagher & Hartley, 2017; Giannelli & Canessa, 2022; Hoffmann et al., 2024). However, an important feature of contemporary climate change is increased climate *variability*: households are impacted not only by one-time, high-severity events, but by repeated events that affect their community and other communities around them (Baldwin et al., 2019; Bevacqua et al., 2019; Haile et al., 2020). Managing the impact of correlated risks like these is a throughline of human climate adaptation past and present (Pisor et al., 2022, 2023).

Here, we demonstrate why researchers and policymakers focused on household-level climate adaptation should look beyond coarse-grained predictors of climate adaptation, like experiencing one or more climate events in the last months or in the last years, and consider the role of temporal and spatial patterning of climate events in household decision-making. We focus on remittances, which we define as transfers of money or goods by an individual to family (or friends) from a location away from the community, either within or between countries. Globally, remitters sent or brought back $794 billion dollars of remittances in 2022 alone (Lionell, 2023), including in response to climate impacts (Bendandi & Pauw, 2016), exceeding foreign direct investment and official development aid (Milpass, 2022). Given increasing frequency of drought globally and increasing spatial extent of drought in Sub-Saharan Africa (Trisos et al., 2022), we examine the impacts of drought conditions on remittances in six African countries in World Bank data from 2009-2010. We find that the average severity of droughts experienced by households predicts receiving a remittance, as does their average spatial extent. In other words, it seems that households may be deploying a key climate adaptation not just in response to single events, or how bad events are on average, but in response to patterning that may change not just how the household, but also their neighbors and neighboring communities, are affected.

1.1 How patterning matters for household-level adaptation

When investigating household-level adaptation, researchers often focus on responses to single, severe events – typically called *shocks* in the development literature. For example, much of the literature on climate and migration (Cattaneo et al., 2019; Kaczan & Orgill-Meyer, 2020) and climate and remittances (Bettin et al., 2025; Giannelli & Canessa, 2022; Habib, 2022; Lucas & Stark, 1985) focuses on responses to single, severe events. Single events lend themselves to measurement of resilience, as they can serve as natural experiments, allowing researchers to measure how long it takes households to return to pre-shock levels of income, for example (Deryugina et al., 2018; Gallagher & Hartley, 2017). International datasets have likewise focused on single events, with large-scale studies like World Bank's Living Standards Measurement Study only recently shifting focus to ask participants about the onset and duration of events in the last year (Contreras et al., 2023; World Bank Group, 2025). As variability and multivariate hazards are increasingly a feature of climate change (Zscheischler et al., 2020), focus on single, severe events paints only a partial picture of the experiences that guide household adaptation.

Patterns matter for household perceptions of climate risks and related decision-making (Agrawal, 2010; Ember et al., 2020; Halstead & O'Shea, 1989; Pisor et al., 2022, 2023; Thornton & Manasfi, 2011). Subsistence peoples in 96 countries report increased duration and severity of climate events and changes in their predictability (Savo et al., 2016). Events can cluster, especially in certain modes of climate variability like El Niño or La Niña (J. Singh et al., 2022), amplifying the effect of individual hazards on households by limiting the time to recover and respond. Events with large spatial extent can undercut risk-management networks, like microloan associations, across neighboring households and communities (Fafchamps & Lund, 2003; Pisor & Jones, 2020). Importantly, these features of climate events often co-occur: communities experience clusters of high-severity events, or frequent events with large spatial scale, compounding the hazards they face (Raymond et al., 2020; Zscheischler et al., 2020).

Drawing on our previous work (Pisor et al., 2023), we identify four components of climate variability that affect which adaptations household use, as captured by the social, ethnographic, and archaeological literature. Severity – which, depending on the climate hazard in question, can include duration, intensity, and magnitude – and temporal autocorrelation, or clustering of events, both often exhaust local means for buffering climate risk, including savings and mutual aid (Few et al., 2021; Halstead & O'Shea, 1989; Pisor et al., 2023). High frequency events can have similar effects, and importantly, households may not have local adaptations in place for low-frequency events (Minnis, 1985; Whitehead & Richerson, 2009); for example, for households that do not have diversified income streams – one form of adaptation – single climate events can be predictive of first-time labor migration (Carrico & Donato, 2019) that enables later remittances in response to household need (de Brauw et al., 2013). Spatial extent means spatial correlation in the experience of climate impacts, such that mutual aid networks – including those that provide remittances – can be simultaneously impacted (Jones et al., 2021; Pisor & Surbeck, 2019).

1.2 Why focus on droughts and remittances

Droughts are a key threat to human well-being in the 21st century. Drought frequency, duration, spatial extent, and severity have already increased globally, including in many regions of Africa (Masih et al, 2014), and are expected to increase further (Eitelweing et al., 2024; Touma et al., 2015; Trisos et al., 2022). Droughts have historically had both short- and long-term impacts on human health, via impacts on e.g., water supplies, food production, and heat stress (Toreti et al., 2024); even if droughts are well-forecasted, many governments in Africa have few resources to address these impacts (Masih et al., 2014). From 1900-2013, droughts in Africa led to 800,000 deaths and 362 million people were affected (Masih et al., 2014), with an additional 2,400 deaths and 275 million people affected since 2013 (CRED / UCLouvain, 2025; Delforge et al., 2023).

Remittances can be a stabilizing force for household income (Amuedo-Dorantes & Pozo, 2011; Premand & Stoeffler, 2022) and can be used as an adaptation in reaction to and in anticipation of climate events like droughts (Maduekwe & Adesina, 2021; Makhlouf & Selmi, 2024; Musah-Surugu et al., 2017), although they fulfill many other household needs as well (Cohen, 2011; Entzinger & Scholten, 2022). For example, remittances may be used for risk-management solutions like air conditioning, livelihood diversification, and flood management, to name a few (Bendandi & Pauw, 2016; Lucas & Stark, 1985; Musah-Surugu et al., 2017; A. T. Tapsoba et al., 2019). Importantly, remittances vary in how costly they are to a household: receiving remittances from household migrants suggests the household first invested in labor migration, a cost not associated with receiving remittances from non-household migrants (de Brauw et al., 2013; Hoddinott, 1994). International migration can be especially expensive (Hunter et al., 2015). Taken together, remittances are a subset of risk-pooling strategies that include gifts, mutual aid, and microloan collectives (Aktipis et al., 2018; Pisor et al., 2023) and take place in the context of long-distance social relationships, which tend to provide nonlocal resource access (Pisor & Ross, 2022; Pisor & Surbeck, 2019).

1.3 Our predictions

Considering patterning in the temporal and spatial components of climate impacts, like drought, and the use of non-local strategies like remittances for risk management, we hypothesize that remittances should be more common when droughts have:

H1: High severity

H2: High frequency

H2: High temporal autocorrelation

When the severity of a series of events is higher or events are more clustered or recurrent in time, households are likely to deplete adaptations that are primarily local, like savings and livelihood diversification. Likewise, remittances should be more common when climate events have:

H4: Large spatial extent

Widespread impacts mean that local social safety nets will be less able to buffer risk; households will rely on partners farther away.

We test these hypotheses with World Bank data, examining receipt of at least one remittance over the last 12 months, and satellite and weather station data for six African countries, focusing on drought as measured by 3-month moisture deficit (precipitation minus potential evapotranspiration) anomalies with the Standardized Precipitation Evapotranspiration Index (SPEI). We classify a drought event as having occurred when moisture deficits fall below the 10th percentile of the 1981-2009 climatological distribution.

We examine these hypotheses further in exploratory analyses: First, because the intervals over which drought impacts are salient may vary, we vary time period and SPEI length. Second, we examine characteristics of the remitter – whether they are a household member, when they moved, and where they are located – to explore whether households invest in labor migration in response to climate impacts, to gain access to remittances.

2. Methods

2.1 Data

2.1.1 Study locations

All sub-Saharan African countries in this study – Burkina Faso, Kenya, Nigeria, Senegal, South Africa, and Uganda – experienced droughts in the early 2000s with environmental and socioeconomic impacts (Masih et al., 2014). Most notably, Kenya had an unprecedented drought (2008-2011), impacting 3.7 million people and leading to US$12.1 billion in losses and damages (Global Facility for Disaster Reduction and Recovery, 2012). In 2002, Senegal experienced a short but impactful summer drought, diminishing crop yields by ~75% (Global Facility for Disaster Reduction and Recovery, 2011). A severe drought in Uganda in the early 2000s caused food shortages for 600,000 people (UN News, 2005) and hydroelectric power reductions in 2005 (The New Humanitarian, 2005), and Burkina Faso was in a "quasi-drought" state throughout the 2000s (Crawford et al., 2016).

International remittances were a stable source of income smoothing in sub-Saharan Africa in the 2000s (Gupta et al., 2009; R. J. Singh et al., 2011). In Senegal, Nigeria, and Uganda, international remittances were substantial from 2005 to 2009, comprising between 3-8.4% of GDP (World Bank Open Data, 2025). In US dollars, Nigeria received more remittances than any other African country from 2005-2009, and Kenya, Senegal, South Africa, and Uganda were in the top 10 (World Bank Open Data via Intelpoint,

$SVI_{t,i,j}$

2025). Burkina Faso is the outlier – migrants had returned due to a civil war in Ivory Coast from 2002-2007, but remittances were growing again in 2009 (T. A. Tapsoba & Hubert, 2022).

2.1.1 Social data

Data from the World Bank African Migration and Remittances Surveys include 16,898 observations of remittance senders to 11,766 households across Burkina Faso, Kenya, Nigeria, Senegal, South Africa (all in 2009), and Uganda (in 2010)(*Migration and Remittances Surveys*, n.d.).

AP and HJ inferred household latitude and longitude by matching administrative level names provided in the survey with locations from Google Maps and MapCarta, with checks from ChatGPT. DT calculated distance from the household to the nearest population center using nighttime lights data from the National Oceanic and Atmospheric Administration (NOAA)-National Geophysical Data Center, processed by Hall and colleagues (2019) using an azimuthal equidistant projection to estimate unplaced population centroids at administrative level 1.

2.1.2 Climate data

To identify droughts, we use the Standardized Precipitation Evapotranspiration Index (SPEI; Appendix 1)(Vicente-Serrano et al., 2010): positive during wet conditions and negative during dry conditions and typically spanning -4 to 4 standard deviations (SD). This CHIRPS-GLEAM dataset is spatially continuous over land at a 0.05° resolution and provided by the Hydro-JULES NERC-funded research program (S. Gebrechorkos et al., 2023) with precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (*CHIRPS: Rainfall Estimates from Rain Gauge and Satellite Observations | Climate Hazards Center - UC Santa Barbara*, n.d.) and potential evapotranspiration data from the Global Land Evaporation Amsterdam Model (GLEAM) (Miralles et al., 2011). We use the 3-month SPEI, where deficits are calculated by accumulating over the previous 3 months, to capture mild to moderate drought conditions missed by either shorter or longer measures (e.g., 1-month or 12-month deficits) (Zhao et al., 2017). We use 1981-2009 as our climatological period and use the 10th percentile of the climatological 3-month SPEI distribution as our drought threshold, traditionally known as “severe” droughts (Svoboda et al., 2002).

We estimate monthly vegetation health using the Normalized Difference Vegetation Index (NDVI) from the NOAA Climate Data Record (CDR) of AVHRR Normalized Difference Vegetation Index (NDVI), Version 5 (Vermote & NOAA CDR Program, 2019), again at 0.05° resolution. However, the locations of pixel centers are different from those of the SPEI data; we use bilinear interpolation to ensure the grid cells are overlapping. We then calculate the Standardized Vegetation Index (SVI) to quantify whether a month is in a relative drought or healthy period compared to its climatological mean, comparable to the SPEI:

$$SVI_{t,i,j} = \frac{NDVI_{t,i,j} - \mu_{ij}}{\sigma_{ij}},$$

where $NDVI_{t,ij}$ is the NDVI in the *t*th month, and *ij* coordinates of the grid point or pixel, μ_{ij} is the long-term mean of the *ij*th point, and σ_{ij} is the standard deviation at that point.

Some household locations (primarily in Senegal) did not have SPEI and NDVI data due to their proximity to the coast. To overcome this, we found the closest land point that did have social data – usually within 10 km away, within the tolerance for drought assessments due to the relatively smooth spatial gradients of drought indices over these distances (e.g., see Global Drought Monitor https://spei.csic.es/map/maps.html).

Data are available at https://github.com/annethro/remittances. For a primer on how to merge climate and social data, see Pisor et al (2023).

2.2 Variables

2.2.1 Outcome

Our outcome is self-reported presence/absence of remittances, whether money or goods, received from household or non-households migrants over the last 12 months. This dataset includes remittances from national or international sources – for example, from mobile banking, by bus, or from Western Union.

2.2.2 Predictors of interest

For the five years preceding and including most interviews (2005-2009), we used the binary time series – presence or absence of drought in a given month, for the grid point where the participant lived – to calculate frequency and severity. As a measure of temporal autocorrelation between droughts, we use an autocorrelation function (ACF):

$$ACF_{t,ij} = \frac{\Sigma\left(\left(x_{t,ij} - \mu_{ij}\right) * \left(x_{t-3,ij} - \mu_{ij}\right)\right)}{\sigma^{2}_{ij}}$$

where $x_{t,ij}$ is the a binary indicator of whether there was drought in the *t*th month at *ij* point; μ_{ij} is the mean drought months for the *ij*th point across the five-year interval; $x_{t-3,ij}$ is the indicator of whether there was drought in the *t*-3th month (given our use of SPEI-3); and σ_{ij}^{2} is the variation for the *ij*th point across the five-year interval. This was calculated using the Python package statsmodels.tsa.stattools.

We calculate severity as follows:

$$Severity_{t,ij} = -\frac{\Sigma\left(P_{10,ij} - y_{tij}\right)}{n},$$

where $P_{10,ij}$ is the value of the 10th percentile at point *ij*, $y_{t,ij}$ is the SPEI-3 for a month *t* and point *ij*, and *n* is the number of months from 2005-2009.

Frequency is the mean number of drought months per year for point *ij*, averaged over 2005-2009.

Spatial extent is the spatially connected area (in km^2) around point *ij* that fell below the 10th percentile threshold at time *t* using image processing tools as in Rastogi et al. (2020) – grid points were counted only if their edges or vertices were touching – and we average spatial extent is averaged across all months from 2005-2009.

2.2.4 Controls

Household wealth. Wealth is calculated per the Demographic and Health Surveys (DHS) wealth index (Rutstein, 2015): items including e.g., building materials, water source, ratio of people to rooms, and market-purchased items are included in a principal components analysis for each country, and the first principal component is extracted. This captures each household's wealth relative to other households in the same country.

Migrant number and household size. Migration and remittances are related. Households often respond to drought by increasing labor migration, which increases remittances in turn. Further, when households are larger, their resource demands are often higher, such that remittances may be in higher demand. As such, we control for both household size and number of household migrants in all models.

Proximity to population center. Population centers represent sources of risk buffering, mobility, and remittance access that can affect results. For example, population centers can provide access to jobs and e.g., Western Unions where remittances may be sent. Nighttime lights data provides good estimates of population size across these six countries, where census data can be inconsistent. We calculate Haversine (as the crow flies) distance from a participant's location to the nearest population center.

Long-term features of ecology. NDVI captures long-term features of local ecology that affect human livelihoods, like land productivity and likely mode of production (e.g, pastoralism or dryland farming when NDVI is lower). As an index of productivity we use the monthly NDVI for a participant's location averaged over 2005-2009.

2.2.5 Random intercepts

Observations are clustered by interview date, census tract, and country: Interview date may capture unobserved variation due to seasonality and shifts in political and social climate, census tract local availability of wealth and social support, and country research protocol, country-level constraints or enablers of remittances, overall financial situation, or interview language. Including random intercepts for date, census tract, and country enables pooling, such that estimates for a cluster with more observations inform estimates for a cluster with less, and clusters in turn inform population-level estimates and individual-level predictions extracted from the model (Bürkner, 2017; McElreath, 2020).

2.3 Statistical analyses

Data was processed using Python (3.12.2) and R (4.4.3) (R Core Team, 2025). Models were run and figures and tables produced in R using packages including brms (Bürkner, 2017) and tidyverse (Wickham et al., 2019). We used Bayesian multilevel logistic regressions (a.k.a. Bayesian hierarchical models) (McElreath, 2020; Qian et al., 2010). Continuous variables were centered and z-scored prior to model fit.

Models were run for 4,000 steps across 4 chains with a 2,000-step burn in. Each model fit was checked for convergence (R-hat) and effective sample size; R-hats did not exceed 1.01 and effective sample size was never below 100 times the number of chains (n=400) (Stan Development Team, 2024a). We conducted posterior predictive checks for each model (e.g., Figure S2). A Bayesian pseudo-R^2 (Gelman et al., 2019) is reported with each plot of model results (e.g., Figure 2). Code is available at https://github.com/annethro/remittances.

Our models use weakly regularizing priors. Environmental variables (i.e., drought severity, frequency, autocorrelation, and spatial extent, and ecological productivity) are understandably correlated at moderate levels (Figure S1). As this could create ridges in the posteriors for our model estimates, we set the priors for predictor variables to a normal distribution with constant variance to avoid ridges (Stan Development Team, 2024b). Indeed, bivariate plots of the relationship between the posteriors of moderately correlated variables show no signs of ridges (Figure S2).

2.3.1 Robustness checks

2.3.1.1 Time window

People's responses to changed climate impacts may reflect their recall of events and recovery from previous events. On recall and timing: global migration data show a lag of between 6-15 years between a given drought and outmigration (Hoffmann et al., 2024), and analysis of US social media posts suggests that people's baseline expectations for climate reflect conditions two to eight years ago (Moore et al., 2019). On recovery, there are often increases in remittances immediately following disasters (Bettin et al., 2025; Giannelli & Canessa, 2022; Habib, 2022), and following a disaster like Hurricane Katrina in the US, communities often recover financially within five years (Deryugina et al., 2018; Gallagher & Hartley, 2017).

Given the immediate responsiveness of remittances to high-severity events, the salience of information from 2-15 years ago in perceptions and decision-making, and financial recovery within approximately five years, we use a five-year time window for our main model and a ten-year window in a robustness check.

2.3.1.2 Thresholds

As we outline in a recent paper (Pisor et al., 2023), we recommend thresholding that does not rely on absolute values but rather (1) percentiles of the observed distribution for a gridpoint, (2) a known magnitude for the region, or (3) specified return intervals (e.g., "20-year rainfall event"). Here, we focus on percentiles of the observed distribution: this flexible approach is appropriate for wide-scale applications like ours and does not assume normality. However, as SD of SPEI is commonly used as a threshold in the literature, we run a robustness check with a -1.5 SD threshold.

2.3.1.3 SPEI length

While a 3-month SPEI performs better than longer timescales at capturing mild to moderate drought and impacts on major crops, 12-month SPEI correlates more strongly with the Palmer Drought Severity Index (PDSI) and captures longer-term impacts on water tables (Zhao et al., 2017) and soil moisture (Törnros & Menzel, 2014; Vicente-Serrano et al., 2012). Accordingly, we run a robustness check with SPEI-12, calculating temporal autocorrelation with a lag of 13.

2.3.1.4 Severity in agricultural drought vs severity in vegetation health

SPEI and SVI are two common metrics for triangulating drought presence or absence, so we explore SVI as an alternate measure of drought. As with the SPEI, the SVI is negative when vegetation health is relatively "unhealthy" or in a drought.

2.3.1 Exploratory analyses

To better understand the relationship between characteristics of drought and use of remittances, we conducted exploratory analyses of whether different characteristics of drought interact in their effects and whether households responded to droughts with migration, better positioning them to receive remittances.

2.3.1.1 Send a labor migrant?

Households may choose to send a household member elsewhere or invest in a remittance-sending relationship with a non-household member. We investigate whether predictors from our main model predict receiving a remittance from a household member, a non-household member, or no one. Households with more wealth can more easily send a labor migrant; as with our main model, wealth is included as a control.

2.3.1.2 Decorrelating risk

Given droughts vary in their spatial extent, households may pursue remittances from senders at a greater distance if droughts are higher in their average spatial extent. We fit an exploratory model interacting sender's location (in-country vs out-of-country) and household status (household vs non-household member) with spatial extent to explore whether average spatial extent predicts receipt of out-of-country remittances. Countries vary in geographic size, such that out-of-country entails greater distance for e.g., South Africa vs Uganda; as with our main model, country is included as a random intercept.

2.3.1.3 When did household migration occur?

If households invested in labor migration, did they do so in response to events between 1-5 years before the interview – during the time period of our environmental data and before measurement of remittance receipt (over the last 12 months)? We run a model with a categorical predictor indicating whether the sender moved to their present location (a) five years prior), one to five years prior, or (c) within the last 12 months. Note that the dataset provides a migrant's time at current location only, so we cannot assess whether this was their first outmigration or whether they were at other locations or for how long. South Africa is omitted from the analysis as the time-at-location question was not asked there.

2.3.1.4 Adding a two-way interaction

To preview our results below: severity and spatial extent positively predict receiving a remittance. To understand whether these two variables together predict remittance receipt, we re-fit our main model with a two-way interaction between severity and spatial extent.

3. Results

4824 (40.4%) of 11,776 households received a remittance of money or goods in the last 12 months (Table 1), from an average of 0.7 household or non-household remitters. Remittance receipt was more common in Burkina Faso, Kenya, and Senegal, where approximately half of households received remittances, and less common in Nigeria, South Africa, and Kenya, where between 10-23% of households received remittances (Table S1a).

The range of drought experiences across countries – in severity, frequency, temporal autocorrelation, and spatial extent – is illustrated in Figures 1 and S3. Ugandan households experienced droughts higher in frequency and severity than other countries, while Senegalese households experienced droughts of low severity, frequency, and spatial extent – partially because many Senegalese households were on the coast.

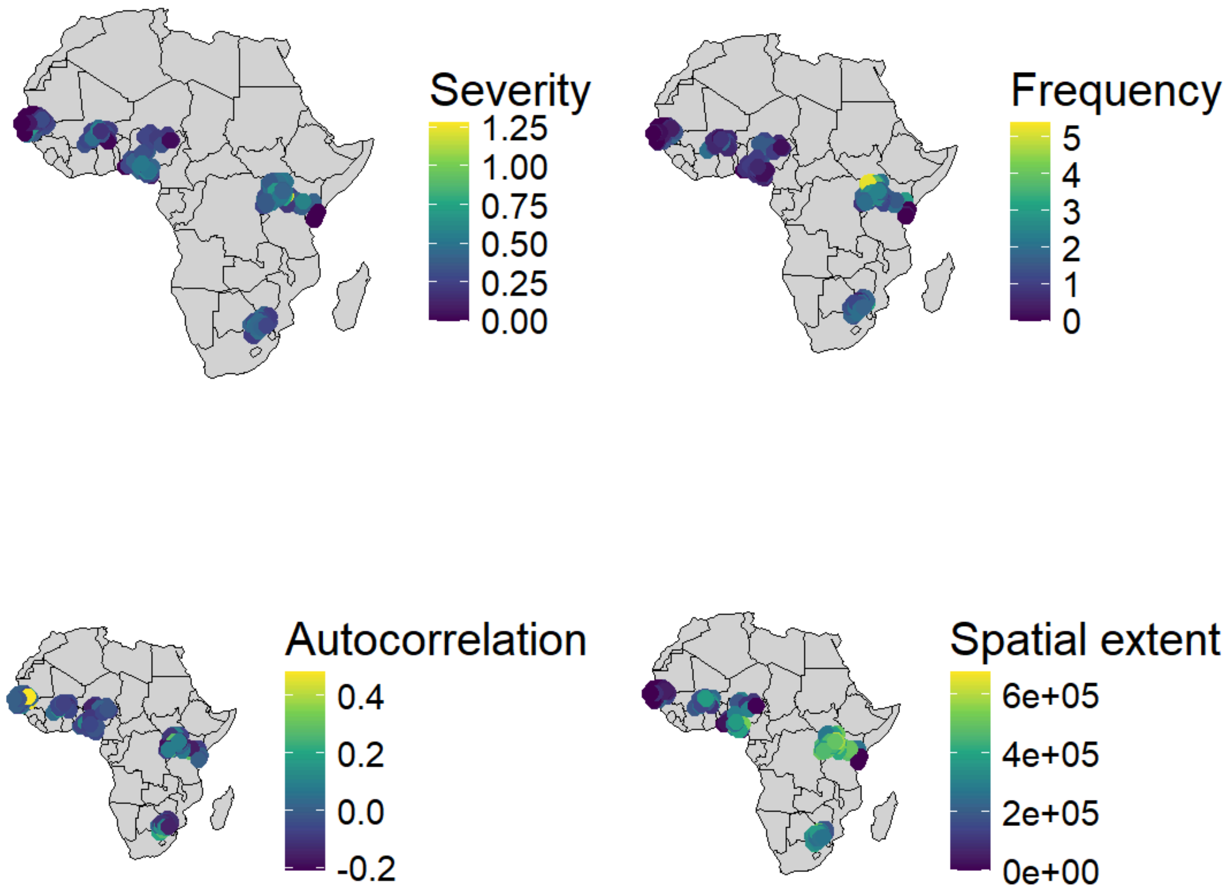
Model results are reported as odds ratios with 90% credible intervals, with results for our main model in Figure 2 and results for our exploratory models/sensitivity checks in Figures S4-S15.

Table 1. Descriptive statistics for households (n = 11,776). Note that all variables are unstandardized in this table except for wealth index, which is standardized by country as it is not comparable across countries.

Variable	Mean	SD	Min	Max
Any remittance (pres/abs)	0.34	0.47	0.00	1.00
Autocorrelation	-0.01	0.12	-0.21	0.48
Dist. to pop. center	6.71	9.50	0.01	71.04
Frequency	1.28	0.91	0.00	5.40
Household size	6.16	4.33	1.00	57.00
Mean NDVI	0.21	0.05	0.04	0.34
Number of migrants	0.99	1.45	0.00	20.00
Severity	0.31	0.17	0.00	1.28

Spatial extent	287,529.67	219,131.77	0.00	1,062,984.62
Wealth index (std.)	-0.03	0.96	-2.75	5.61

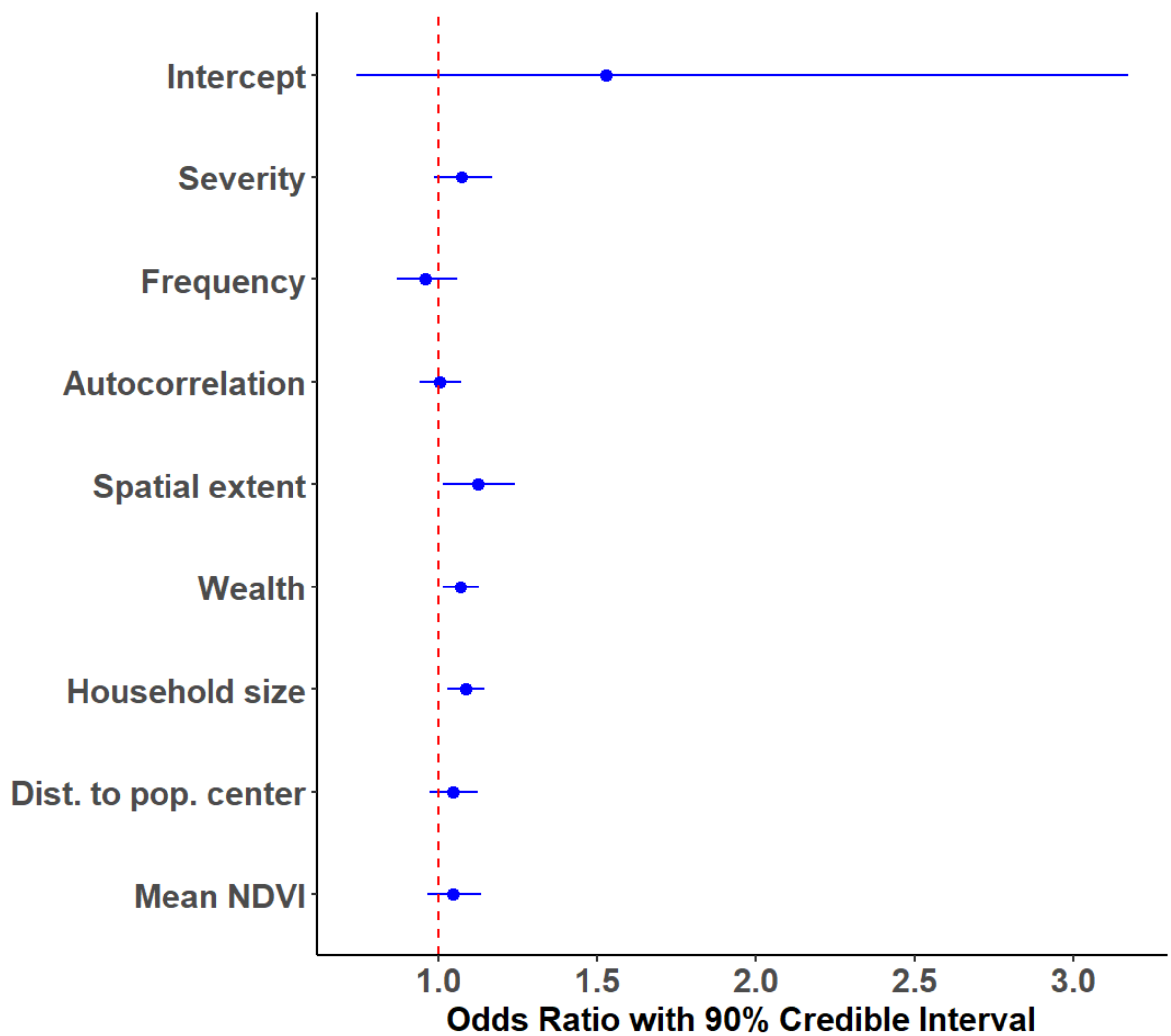
Figure 1. The range of household experiences with frequency, autocorrelation, severity, and spatial extent of droughts across the sample. Units for frequency are in events per year, autocorrelation is a correlation coefficient between -1 and 1, severity is percentage points below the 10th percentile, and area is in km^2.



3.1 Severity

For every one standard deviation (SD) higher severity of drought a household has experienced over the last five years, they are 7% more likely to report receiving a remittance in the last 12 months (odds ratio (OR) = 1.07, 90% credible interval (CI) = 0.99-1.17; Figure 2). This result trends in the same direction when we use a drought threshold of -1.5 SD (OR = 1.05, 90% CI = 0.95-1.16, Figure S4) and when 41 households with values at or above 3 SD of severity (Figure S3) are excluded (10th percentile OR = 1.14, 90% CI = 1.04-1.25, Figure S5; -1.5 SD OR = 1.24, 90% CI = 1.10-1.41, Figure S6).

Figure 2. Results from our Bayesian mixed-effect, logistic model, reported as odds ratios with 90% credible intervals. The model estimate for migrant number is excluded because it makes other estimates difficult to read (OR = 9.78, 90% CI = 8.77-10.91). All continuous variables were standardized prior to model fitting. Bayesian R^2 = 0.32. Random intercepts: interview date (SD = 0.09), country (SD = 1.42), and census tract (SD = 0.88).



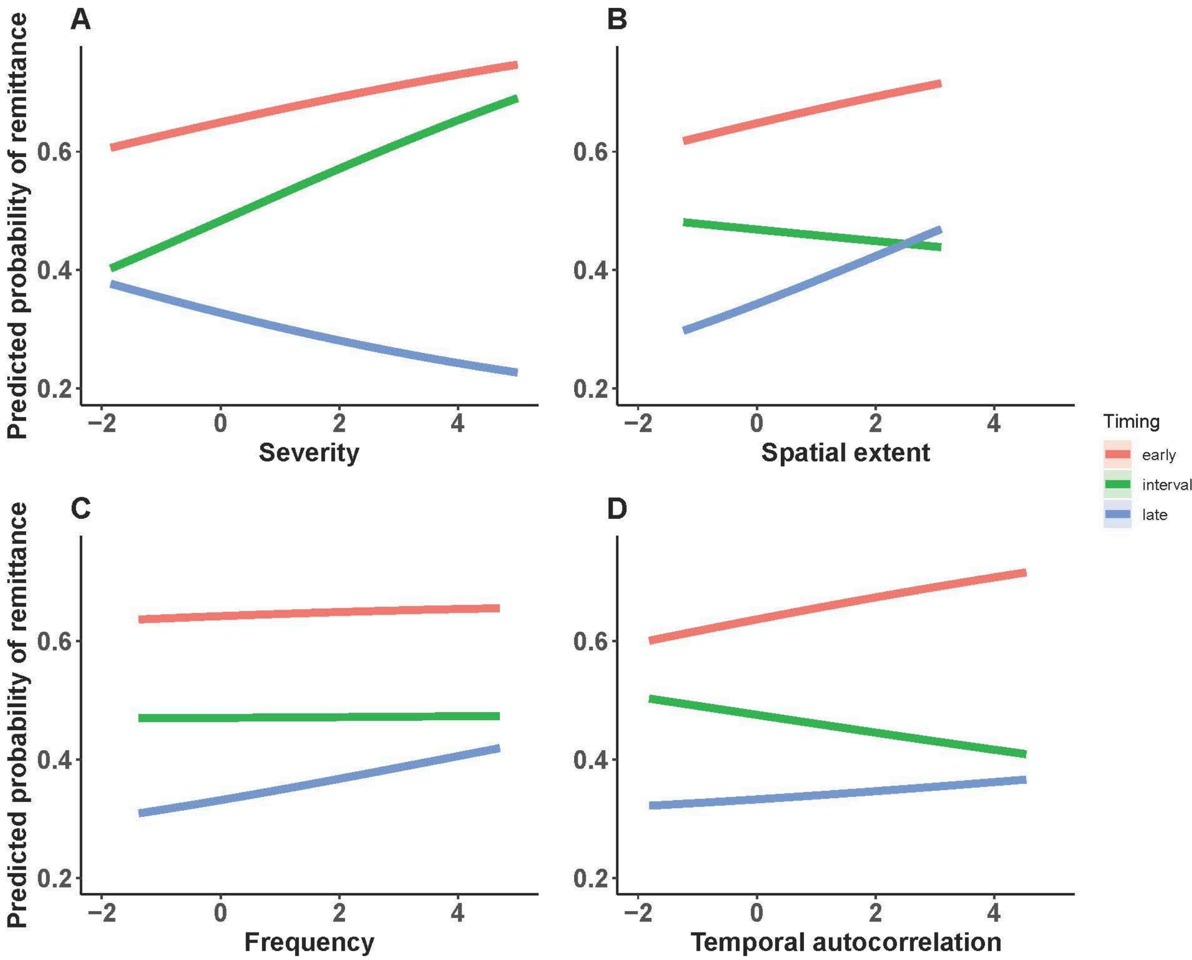
Severity is still a positive predictor when we vary time intervals, considering a 10-year interval (OR

= 1.06, 90% CI = 0.96-1.17; Figure S7) instead of five, and when we consider severity measured with SVI (OR = 1.12, 90% CI = 1.04-1.21; Figure S8) instead of SPEI-3. However, the direction of effect reverses when we consider SPEI-12 (OR = 0.82, 90% CI = 0.73-0.93; Figure S9).

For SPEI-3 over a five-year interval, at higher levels of severity households are especially likely to receive a remittance from a household member (OR = 1.09, 90% CI = 1.00-1.20), but not a non-household member (OR = 1.03, 90% CI = 0.90-1.19), compared to receiving no remittance at all (Figure S10). Household migrants who moved to their current location more than a year ago are more likely to send a remittance if droughts during the last five years have been more severe – especially if the migrant moved more than five years ago (Figure 3a; Figure S11). Household members who moved in the last 12 months are less likely to remit at higher levels of severity.

Migrants do not appear to be moving in response to drought severity over the last five years: relative to households who had a migrant move more than five years ago, households experiencing higher average severity during the last five years were perhaps more likely to have a migrant move 1-5 years ago, with some uncertainty in the model (OR = 1.05, 90% CI = 0.97-1.14), but were less likely to have a migrant move during the last 12 months (OR = 0.84, 90% CI = 0.73-0.96; Figure S12).

Figure 3. Two-way interactions between the four drought characteristics, measured over the last five years, and the timing of a household migrant's last move: five or more years ago (early); one to five years ago (interval); or within the last year (late). Predicted probabilities are calculated from parameter estimates across standardized values for severity (A), spatial extent (B), frequency (C), and temporal autocorrelation (D); all other predictors are held at their mean values. See Figure S11 for fit statistics.



3.3 Frequency

There is no relationship between frequency and reporting receiving a remittance regardless of whether we use a 10th percentile threshold (OR = 0.96, 90% CI = 0.87-1.06; Figure 2), a -1.5 SD threshold (OR = 0.94, 90% CI = 0.83-1.07; Figure S4), or consider SPEI-12 (OR = 0.96, 90% CI = 0.86-1.08; Figure S9) instead of SPEI-3. If we consider a ten-year interval instead of a five-year interval, increased frequency of droughts may negatively predict receiving a remittance, though our model is somewhat uncertain (OR = 0.90, 90% CI = 0.80-1.01; Figure S7).

This negative relationship may be related to non-household migrants: at one SD higher frequency over the five-year interval, non-household migrants are 25% less likely to send a remittance (OR = 0.75, 90% CI = 0.63-0.89; Figure S10), while household migrants are no more or less likely to send a remittance (OR = 0.98, 90% CI = 0.89-1.09). For household migrants, those who moved in the last year are the most likely to respond to high-frequency droughts by sending a remittance (Figure 3b; Figure S11); however, household migrants are not responding to drought frequency during the five-year interval by moving (1-5 years ago: OR = 1.03, 90% CI = 0.93-1.14; 0-12 months ago: OR = 1.02, 90% CI = 0.88-1.20; Figure S12).

3.4 Temporal autocorrelation

There is no relationship between temporal autocorrelation and reporting receiving a remittance when we use a 10th percentile threshold (OR = 1.00, 90% CI = 0.94-1.07; Figure 2), though it does predict receiving remittances when we use a -1.5 SD threshold, with some uncertainty (OR = 1.07, 90% CI = 0.99-1.15; Figure S4). When we use SPEI-12, temporal autocorrelation is a negative predictor of receiving remittances (OR = 0.91, 90% CI = 0.85-0.99; Figure S9), and when we consider a ten-year interval, it has no effect (OR = 1.00, 90% CI = 0.94-1.07; Figure S7).

Temporal autocorrelation is a positive predictor of receiving a remittance from non-household members, such that a one standard deviation increase in temporal autocorrelation predicts a 16% increased odds of receiving a remittance from a non-household member (OR = 1.16, 90% CI = 1.04-1.30; Figure S10). Overall, household members are no more likely to send more remittances (OR = 0.96, 90% CI = 0.90-1.03), though it depends on the timing of their move: those who moved before the five-year interval or during the last 12 months are more likely to send a remittance, while those who moved 1-5 years ago are less likely (Figure 3c; Figure S11). For every one SD increase in temporal autocorrelation, households are less likely to report a migrant moving between 1-5 years ago (OR = 0.86, 90% CI = 0.97; Figure S12).

3.4 Spatial extent

Households experiencing one SD greater spatial extent of drought over the last five years are 12% more likely to report receiving a remittance in the last 12 months (OR = 1.12, 90% CI = 1.02-1.24; Figure 2). This effect holds when we use a drought threshold of -1.5 SD (OR = 1.24, 90% CI = 1.10-1.41; Figure S4). However, the result is sensitive to values from Nigeria, where 371 households experienced a spatial extent above 3 SD; when excluded, the result with -1.5 SD threshold holds (OR = 1.22, 90% CI = 1.07-1.38; Figure S6) but the result with the 10th percentile threshold does not (OR = 0.99, 90% CI = 0.85-1.16; Figure S5).

These 371 households all experienced the same average spatial extent of drought and are approximately three times as likely to receive a remittance as other households in Nigeria (Table S2). These households appear to differ from other Nigerian households only in their exposure to high spatial extent and likelihood of receiving remittances: they are similar to other Nigerian households on other dimensions (compare Table S1a), and some of the 371 households are 150 km apart by road, suggesting their day-to-day experiences likely differ. In short, the 371 households are influencing model fit, not biasing it. We include them in the results reported below and discuss them further in the Discussion.

We find that spatial extent is a positive predictor of receiving a remittance regardless of time period – whether we consider patterns of drought over 10 years (OR = 1.12, 90% CI = 0.99-1.27; Figure S7) or use SPEI-12 (OR = 1.12, 90% CI = 0.98-1.28; Figure S9).

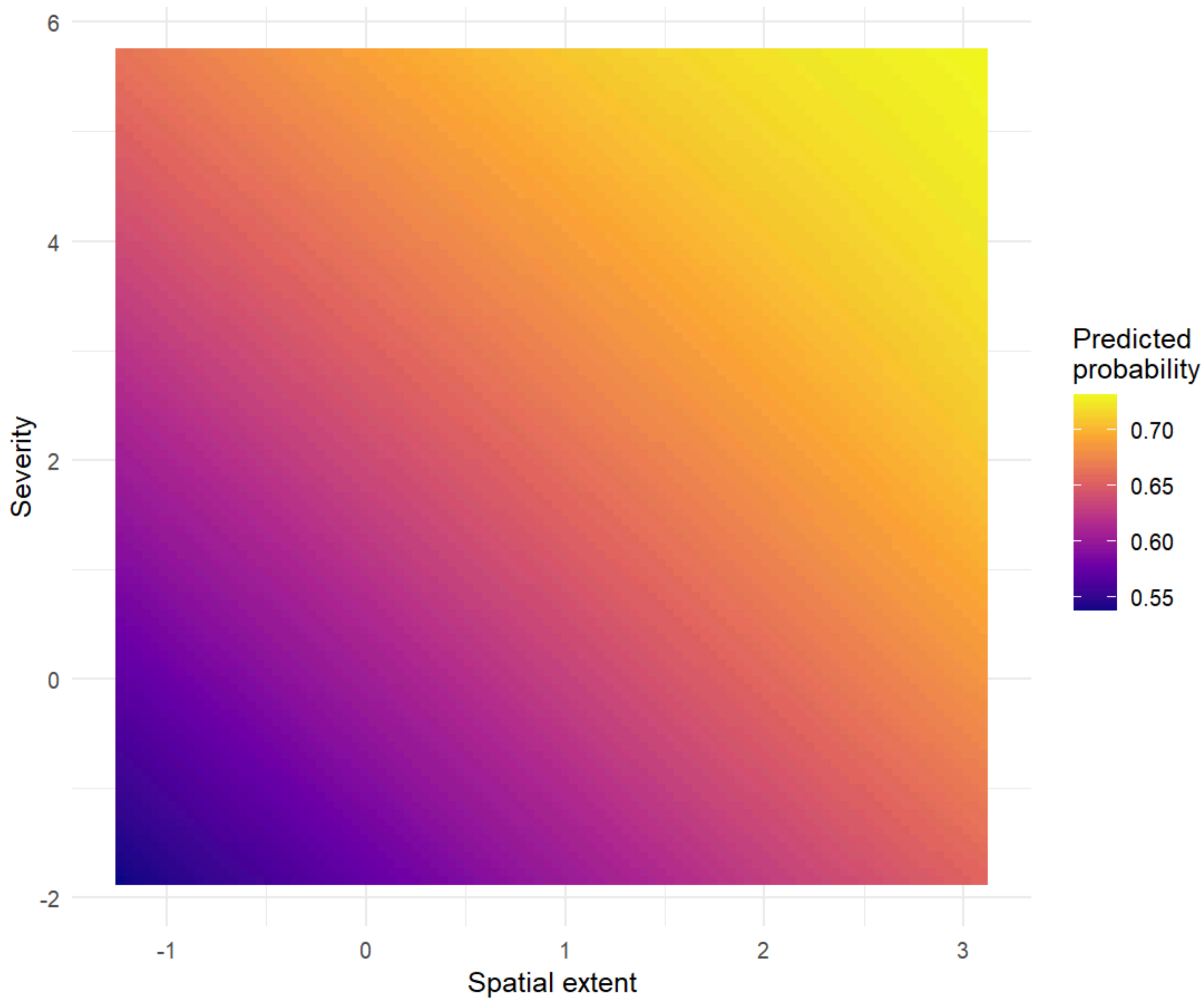
As spatial extent goes up, households are more likely to receive remittances (non-household members: OR = 1.17, 90% CI = 1.00-1.38; household members: OR = 1.11, 90% CI = 1.00-1.24, Figure S10) relative to no remittance at all. Household members who moved to their current location more than five years ago or in the last 12 months are more likely to send a remittance when spatial extent is higher (Figure 3d; Figure S11). However, households experiencing spatially extensive drought were less likely to have a household migrant move during the five-year period (1-5 years ago: OR = 0.78, 90% CI = 0.71-0.86; 0-12 months ago: OR = 0.81, 90% CI = 0.69-0.94, Figure S12) than households experiencing less spatially extensive drought.

For spatial extent specifically, we examine whether households experiencing high spatial extent are more likely to rely on international remittances – which are more likely to be beyond the scope of drought. In general, households are more likely to report remittances that are international vs national in origin, regardless of the average spatial extent of droughts or whether the sender is a household or non-household member (Figure S14). However, as spatial extent increases, senders who live nationally are slightly more likely to send a remittance, though the effect is modest (Figure S14).

3.5 What about the combination of severity and spatial extent?

To understand whether severity and spatial extent could *together* affect households' likelihood of receiving a remittance, we fit an exploratory model with a two-way interaction between severity and spatial extent. Households are most likely to report receiving remittances when they are experiencing high spatial extent and high severity droughts (Figure 4); the predictor for the interaction term does not differ from an odds ratio of 1 (OR = 1.00, 90% CI = 0.93-1.06; Figure S15).

Figure 4. The predicted probability of reporting receiving a remittance by the interaction between average drought severity and average spatial extent. All other fixed-effect variables are set to their mean values and all variables were standardized prior to model fitting. The parameters for this model appear in Figure S14.



3.6 Key controls

Note that two controls one would expect to predict receiving a remittance – number of household migrants currently away and household wealth – both predict receiving one. Number of household migrants is an outsized predictor of receiving remittances (OR = 9.78, 90% CI = 8.77-10.91) – so much so that it is not shown in Figure 2, as it makes other results difficult to see. Wealth is also a predictor of receiving remittances (OR = 1.07, 90% CI = 1.02-1.13; Figure 2), especially from a household migrant (OR = 1.10, 90% CI = 1.04-1.17; Figure S9), but is not associated with the timing of a household migrant's last move (1-5 years prior to the interview: OR = 0.98, 90% CI = 0.93-1.04; 0-12 months prior to the interview: OR = 1.04, 90% CI = 0.95-1.13; Figure S11).

4. Discussion

When studying climate adaptation, researchers have largely focused on responses to single, severe events – understandably so, because not only do extreme events move money and people, but it is often easier to track resilience via return to pre-event baselines. However, as climate change alters the severity, frequency, clustering, and spatial extent of climate-driven events, successful adaptation efforts must account for broader *patterns of events*. Patterning matters for household environmental risk management past and present, but it will matter more moving into the future. Here, we demonstrate that households likely attend to patterns when making decisions about how to manage risk. Among 11,766 households across six sub-Saharan African countries, we find the average severity and average spatial extent of drought events over the last five years can predict whether a household received a remittance in the last 12 months. These effects are driven largely by remittances from household migrants – including by in-country household migrants being more likely to send remittances as spatial extent increases. While households experiencing high severity or high spatial extent are no more likely to send out household migrants, household migrants who already left are more likely to send money when severity or spatial extent are high. This is especially true if the household migrant moved more than five years ago.

Our results are relatively robust to our methodological choices, including whether we use a 10th percentile or -1.5 standard deviation threshold for identifying drought, consider patterning over a five vs ten year time period, or examine the 3-month vs 12-month SPEI. When we considered a 12-month SPEI, severity was negatively associated with a household receiving a remittance, not positively. This suggests that longer-term moisture deficits may affect remittance behavior differently, perhaps because the SPEI-3 can better capture drought initiation and termination (Zhao et al., 2017) and seasonal droughts (3-month to 6-month SPEI) are more correlated than annual droughts (12-month SPEI) with agricultural productivity (Chen et al., 2020, 2024; Peña-Gallardo et al., 2019). The effect of spatial extent was sensitive to the inclusion of 371 households from Nigeria experiencing average spatial extents above 3 standard deviations; when these households were excluded, spatial extent predicted remittances only when we considered a threshold of -1.5 standard deviations rather than the 10th percentile. Beyond their experience of high spatial extent and their high probability of receiving a remittance, however, these households look similar to other households in Nigeria (compare Tables S2 and S1b), suggesting that these households are influencing model fit but not biasing it. Moreover, as extreme climate events become more common (e.g., Weitzman, 2011), subsamples of households with extreme exposures – like these 371 households – are likely to become more commonplace in social and environmental data.

Unsurprisingly, several of our control variables were also predictive of receiving a remittance. The number of migrants in each household had an outsize effect, particularly as labor migration tends to precede the arrival of remittances (Giannelli & Canessa, 2022; Musah-Surugu et al., 2017). We find that household migrants who last moved prior to the five-year window were more likely to remit in response to severe or high spatial extent droughts than were migrants who moved more recently – likely because there is often a delay following a move before a migrant is able to send money (Cohen, 2011). However, we find that households that experienced droughts with high severity, high autocorrelation, or high spatial extent are less likely to have a household migrant move in the 0-12 months prior to the interview;

though we cannot distinguish first-time labor migrants from migrants who are on their second or third move, this finding is in line with work by other researchers who find that the short-term impact of drought on household finances makes it more difficult to fund relocation of a household member (Hunter et al., 2013).

Households that were wealthier relative to others in their country were more likely to have received a remittance. While remittances are often predictive of household wealth (Maduekwe & Adesina, 2021; Szabo et al., 2022) and of adaptation in place, like e.g., capital investments in agricultural land and household appliances captured in our measure of wealth (Bendandi & Pauw, 2016; Lucas & Stark, 1985; Musah-Surugu et al., 2017; A. T. Tapsoba et al., 2019), one of our models suggests that migrant movement does not predict household wealth. Wealth at the time of interview is unrelated to whether a household migrant moved more than five years prior, 1-5 years prior, or in the last year (Figure S12). This partially speaks to the possibility of social-class effects, as we do not see evidence that household migration – which must precede remittances from household members – predicts household wealth 0-5 years later.

4.1 Limitations

While the patterns we uncover here are suggestive, the household data we use are cross-sectional (*Migration and Remittances Surveys*, n.d.). We are thus unable to assess causal relationships – for example, (1) whether households are more likely to receive remittances when they do not receive aid (e.g., Musah-Surugu et al., 2017), especially as information on aid is unavailable in these data, or (2) between hydroclimatic patterns and hedonic adaptation, such that shocks may become less aversive when repeated by changing reference levels (Frederick & Loewenstein, 1999) and related subjective well-being (Graham & Oswald, 2010). When possible, future work should leverage panel or longitudinal data on remittance behavior and its responsiveness to hydroclimatic patterns, similar to existing work tracking the impacts of one-time disasters on remittance behavior (Bettin et al., 2025; Giannelli & Canessa, 2022; Habib, 2022).

Household data were collected across six countries by six different research teams; unsurprisingly, there are some differences in these data that required adjustments and assumptions on our part. For example, we had access to municipality names but not census tract for South Africa; three countries lacked date of interview, an important control for potential impacts from seasonality and political climate; and some data were missing. We flag these limitations in our code files and use various strategies to correct for them, including pooling estimates by census tract and country and imputing missing values.

Creating large environmental datasets involves incorporating data that may have errors, using estimation to achieve global coverage, and algorithms that boost the signal-to-noise ratio. To triangulate conditions on the ground, we and other Earth scientists favor triangulation across multiple datasets. For example, among the datasets we use here, NDVI is calculated from daily, atmosphere-corrected, bidirectional surface reflectance from the top of the canopy retrieved from NOAA AVHRR satellites and can suffer from errors in the sensors themselves, the atmospheric corrections implemented to overcome irregularities in the atmosphere, and the exclusion of pixels with clouds (Franch et al., 2017). CHIRPS precipitation is estimated using a combination of station data, which can suffer from collection errors, and satellite data. These data can have similar issues to NDVI. CHIRPS also relies on an algorithm to combine datasets, which is likewise imperfect and uncertainties can change over time and over different locations due to station and satellite data availability. Further, the SPEI dataset relies on an estimation of potential evapotranspiration calculated using a land evaporation model (GLEAM) that integrates satellite and reanalysis data, which can have its own uncertainties (Miralles et al., 2011).

4.2 Future directions

Beyond the relationship between drought characteristics and remittances, we also need to better understand the relationship between other climate impacts and household-level adaptation – for example, between patterned drought and adaptations like livelihood diversification and savings, between patterned floods and remittances, or between compounding, patterned shocks and household strategies (see also Pisor et al., 2022). A more systematic understanding of how patterning impacts household strategies will help us better support different adaptations that work well under different conditions.

For example, while droughts have large impacts on humans, recent floods in Africa have also led to devastating impacts through destruction of property and infrastructure, cropland, and community amenities (Trisos et al., 2022). Given that floods have different temporal and spatial scales than droughts in terms of climate processes as well as impacts, we should not necessarily expect similar dynamics between flood characteristics and the probability of remittances. For example, while high frequency and high autocorrelation in both floods and droughts may predict receiving remittances given decreased recovery time between events, the spatial extent of floods may be less predictive of remittances due to the relatively smaller footprint of floods than droughts. We will explore these mechanisms in future work.

The data come from 2009-2010 and the severity of climate-induced impacts is accelerating (S. H. Gebrechorkos et al., 2025; Spinoni et al., 2014). There is considerable uncertainty regarding where drought frequency and extent is expected to get worse, especially depending on the metric used (e.g., SPI vs. SPEI), but growing consensus suggests increasing drought severity in southern Africa and parts of East Africa (S. H. Gebrechorkos et al., 2025; Gimeno-Sotelo et al., 2024; Haile et al., 2020; Trisos et al., 2022; Vicente-Serrano et al., 2022; Yohannes et al., 2025). Documenting and evaluating the efficacy of household and community responses to changing drought is an important research goal moving forward.

Moreover, developing better, theoretically-supported understanding of the process of adaptation in changing environments is essential. In their exposition of the notion of radical uncertainty, the economists Kay & King (2020, p. 346) note that economic models relegate “almost everything of interest” to shocks, which are by definition external to the data-generating process. They suggest that what is missing in economic models is narrative reasoning of how changes actually come about. This argument applies to adaptation as well. People do not simply cope with shocks, but develop adaptive strategies for survival in patterned environments. The study of adaptation must explain both the pattern and the (successful or unsuccessful) response of people to the emerging patterns.

Here, we focus largely on the location of remittance receivers rather than remittance senders, though there is reason to think that remittance senders are especially likely to be in an area with uncorrelated or negatively correlated environmental risk. Evidence suggests that individuals attend to both climate experiences in origin and destination when making migration decisions (Hoffmann et al., 2024); we should similarly expect that people will attend to where remittance senders are located, perhaps even preferentially engaging in remittance relationship with partners residing in areas with uncorrelated risk. For example, the overall gradient of migration from rural to urban areas in Africa likely reflects household strategies to diversify risk and insure themselves via remittance receipt, as sources of volatility in urban and rural areas are often quite different (de Brauw et al., 2014). Therefore, we stipulate that while droughts drive the need to receive remittances, households are much more likely to receive them if they have social or familial connections in areas that are not affected by a given drought or are better buffered from its effects – and if they do not already have connections in these regions, they may encourage household members to migrate there. Future work will explore this possibility.

Author contributions

Conceptualization: AP, DT, JHJ. Data curation: AP, DT, HJ. Formal analysis: AP, DT. Investigation: AP, HJ. Project administration: AP. Visualization: AP. Writing – original draft: AP, DT. Writing – review & editing: JHJ.

Declaration of Interests

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.

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Supplementary Material

Appendix 1

Drought definitions

From 1900-2013, EM-DAT reported 291 droughts over Africa - while the monetary damages are relatively small compared to other continents, the number of deaths and number of people affected are disproportionately large (Masih et al., 2014). In the first decade of the 2000's, Burkina Faso (2001), Senegal (2002), Kenya (2004, 2005, 2008), Uganda (2002, 2005, 2008) and South Africa (2004), all experienced droughts with significant human and socioeconomic impacts. Droughts in all these cases are identified with different indices and climate variables, different baseline or climatological periods, and using different drought thresholds, making it difficult to assess the impacts from drought systemically. Droughts can be meteorological (precipitation deficit), agricultural (soil moisture deficit) or hydrological (surface water deficits) and different drought indices have been developed to characterize and assess these different types of droughts. Additionally, droughts are defined by setting a climatological period from which to measure deviations from and can impact how droughts are identified. Lastly, a threshold is usually chosen from the distribution of the baseline period (either a percentile or standard deviation) to establish when a certain location is experiencing a drought (Trenberth et al., 2014).

Choice of SPEI

The SPEI reflects agricultural drought by estimating moisture deficits in soils by assessing both the atmospheric supply (precipitation) and demand (potential evapotranspiration) of water. Soil moisture observations are sometimes only surface level (e.g., from satellites), and sometimes temporally and spatially sparse (e.g., from soil-observing networks) - therefore, using the SPEI allows us to overcome these deficiencies. Moreover, the SPEI since it has been shown to correlate well with in-situ measurements of soil moisture in the Middle East (e.g., Törnros & Menzel, 2014) and North America and with global crop yields (e.g., Vicente-Serrano et al., 2010), giving us confidence to use this index to understand impacts on human behavior. Generally, the SPEI has been found to perform better than other drought indices at capturing short-term drought and impacts on water supply (e.g., Hoffmann et al., 2024).

Figure S1

Correlation structure between predictors, as we know there can be correlations between environmental variables that can bias model fit; the _s on each indicates that these variables were standardized. Some variables exhibit moderate levels of correlation, including NDVI mean, spatial extent, frequency, dispersion, and severity. The biggest concern would be ridges in the posteriors for our model estimates between two or more environmental variables; accordingly we set the prior for each environmental variables to a normal distribution with constant variance to avoid ridges (Stan Development Team, 2024b).

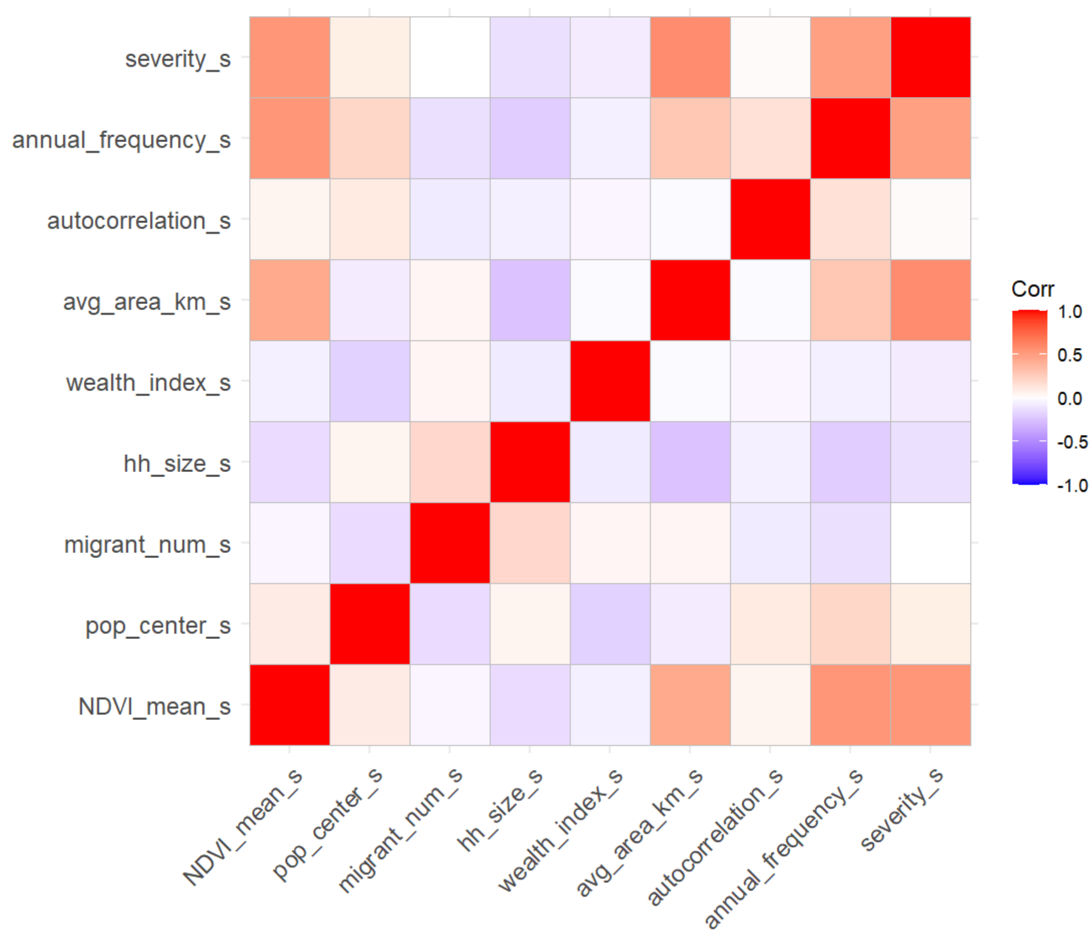


Figure S2

Posterior check of our main model fit. On the diagonal are histograms of draws from the posterior distribution for each environmental variable. Bivariate relationships between the posterior distributions of moderately correlated parameters (see Figure S1) appear on the off-diagonals; there is no sign of ridges or other issues with model fit caused by these correlations. We also performed this same posterior check on all exploratory and robustness-check models.

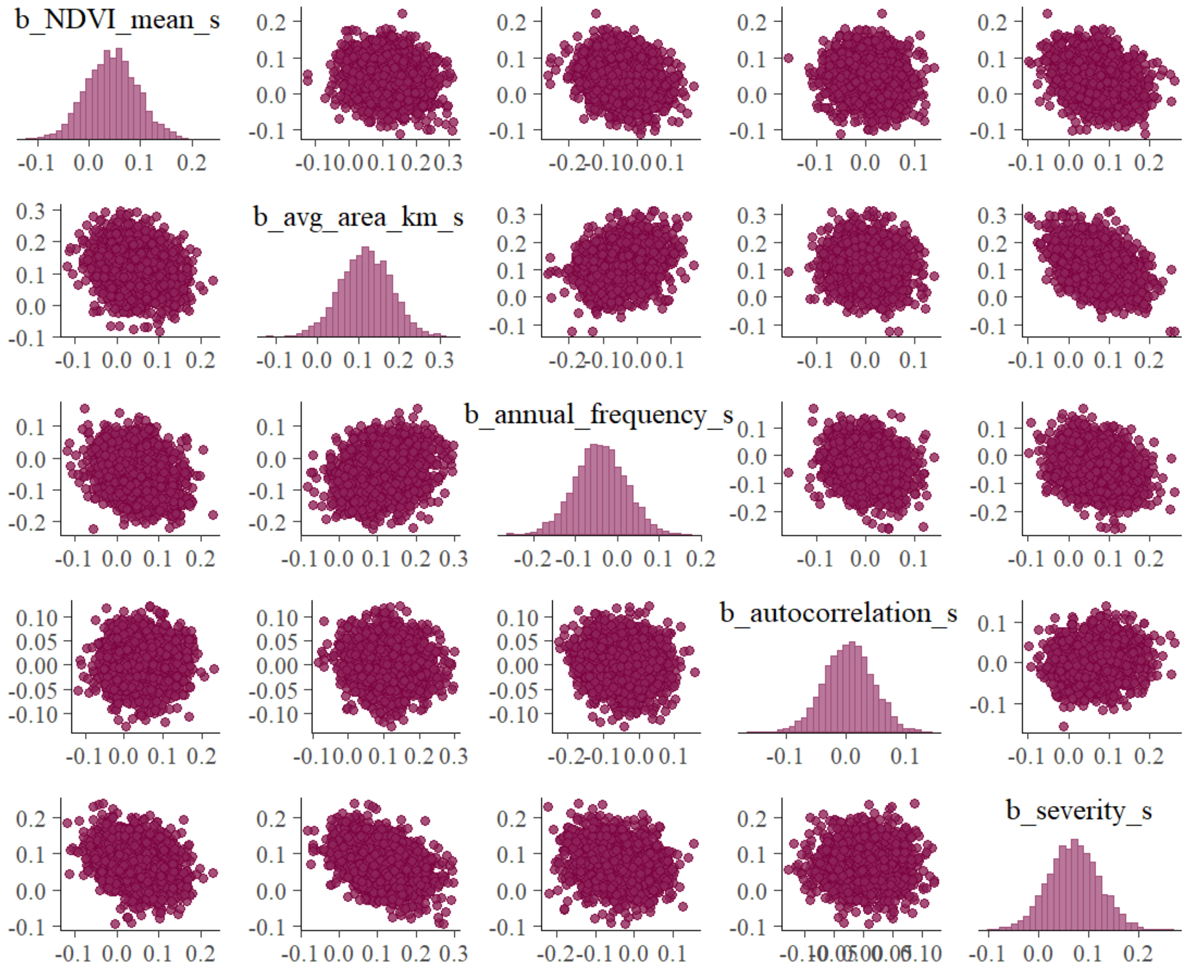


Table S1a

Descriptive statistics by country, **one observation per household** (n = 11,776). Number of **households** by country: Burkina (n = 2102), Kenya (n = 1929), Nigeria (n = 2118), Senegal (n = 1815), South Africa (n = 1950), and Uganda (n = 1862). Wealth index is a standardized measure of wealth created country by country; here we present descriptive statistics for wealth index by country, unlike in the main text, where we report wealth standardized at the sample level to enhance comparability across countries.

Variable	country	Mean	SD	Min	Max
Any remittance (pres/abs)	Burkina Faso	0.53	0.50	0.00	1.00
Any remittance (pres/abs)	Kenya	0.49	0.50	0.00	1.00
Any remittance (pres/abs)	Nigeria	0.19	0.39	0.00	1.00
Any remittance (pres/abs)	Senegal	0.51	0.50	0.00	1.00
Any remittance (pres/abs)	South Africa	0.10	0.30	0.00	1.00
Any remittance (pres/abs)	Uganda	0.23	0.42	0.00	1.00
Autocorrelation	Burkina Faso	-0.05	0.08	-0.16	0.18
Autocorrelation	Kenya	-0.01	0.10	-0.19	0.29
Autocorrelation	Nigeria	-0.04	0.06	-0.16	0.13

Autocorrelation	Senegal	0.02	0.13	-0.12	0.48
Autocorrelation	South Africa	0.07	0.15	-0.15	0.27
Autocorrelation	Uganda	-0.02	0.11	-0.21	0.39
Dist. to pop. center	Burkina Faso	8.37	8.28	0.31	42.89
Dist. to pop. center	Kenya	1.59	2.73	0.05	23.23
Dist. to pop. center	Nigeria	1.02	0.91	0.01	4.43
Dist. to pop. center	Senegal	6.93	9.28	0.44	46.86
Dist. to pop. center	South Africa	14.48	11.28	2.83	65.31
Dist. to pop. center	Uganda	8.24	11.61	0.09	71.04
Frequency	Burkina Faso	1.02	0.46	0.20	2.00
Frequency	Kenya	1.44	0.76	0.00	3.00
Frequency	Nigeria	0.69	0.49	0.00	1.80
Frequency	Senegal	0.41	0.39	0.00	2.00

Frequency	South Africa	1.70	0.32	0.60	3.20
Frequency	Uganda	2.49	0.95	0.80	5.40
Household size	Burkina Faso	8.89	5.00	1.00	36.00
Household size	Kenya	4.22	2.31	1.00	20.00
Household size	Nigeria	5.93	3.26	1.00	24.00
Household size	Senegal	9.18	5.70	1.00	57.00
Household size	South Africa	3.78	2.13	1.00	14.00
Household size	Uganda	4.89	2.77	1.00	16.00
Mean NDVI	Burkina Faso	0.19	0.02	0.14	0.25
Mean NDVI	Kenya	0.22	0.06	0.09	0.33
Mean NDVI	Nigeria	0.19	0.06	0.04	0.29
Mean NDVI	Senegal	0.17	0.04	0.10	0.29
Mean NDVI	South Africa	0.22	0.03	0.17	0.31
Mean NDVI	Uganda	0.25	0.04	0.11	0.34
Number of migrants	Burkina Faso	1.03	1.21	0.00	14.00

Number of migrants	Kenya	1.15	1.33	0.00	9.00
Number of migrants	Nigeria	1.49	2.00	0.00	20.00
Number of migrants	Senegal	1.16	1.38	0.00	13.00
Number of migrants	South Africa	0.18	0.58	0.00	7.00
Number of migrants	Uganda	0.88	1.45	0.00	9.00
Severity	Burkina Faso	0.29	0.09	0.02	0.56
Severity	Kenya	0.30	0.16	0.00	0.59
Severity	Nigeria	0.30	0.18	0.00	0.69
Severity	Senegal	0.15	0.19	0.00	0.97
Severity	South Africa	0.34	0.09	0.14	0.53
Severity	Uganda	0.46	0.14	0.23	1.28
Spatial extent	Burkina Faso	228,516.51	92,237.73	64,162.15	535,204.27
Spatial extent	Kenya	374,660.04	186,014.06	0.00	599,295.90

Spatial extent	Nigeria	331,913.84	364,301.03	0.00	1,062,984.62
Spatial extent	Senegal	35,222.63	41,941.95	0.00	288,724.53
Spatial extent	South Africa	317,727.78	54,876.58	159,647.76	499,277.08
Spatial extent	Uganda	427,710.34	76,075.25	260,745.94	675,437.96
Wealth index	Burkina Faso	0.00	2.16	-1.27	12.09
Wealth index	Kenya	0.00	2.13	-3.79	4.09
Wealth index	Nigeria	0.07	2.13	-5.06	3.56
Wealth index	Senegal	0.01	2.15	-5.80	3.51
Wealth index	South Africa	0.00	1.81	-4.33	3.48
Wealth index	Uganda	0.00	1.93	-3.20	4.22

Table S1b

Continuous descriptive statistics by country, **one observation per remittance sender** (n = 16,898). Number of **observations** by country: Burkina (n = 3716), Kenya (n = 3073), Nigeria (n = 2334), Senegal (n = 2866), South Africa (n = 2107), and Uganda (n = 2802). Wealth index is a standardized measure of wealth created country by country; here we present descriptive statistics for wealth index by country, unlike in the main text, where we report wealth standardized at the sample level to enhance comparability across countries. We do not include descriptive statistics for drought characteristics as some households have more than one observation (row), biasing estimates for mean and standard deviation.

Variable	country	Mean	SD	Min	Max
Migrant months in current location	Burkina Faso	97.44	93.18	1.0	797
Migrant months in current location	Kenya	75.30	79.36	1.0	672
Migrant months in current location	Nigeria	68.08	68.50	1.2	660
Migrant months in current location	Senegal	89.02	91.67	1.0	828
Migrant months in current location	Uganda	69.43	78.41	0.0	722
Remittance from specific migrant (pres/abs)	Burkina Faso	0.55	0.50	0.0	1
Remittance from specific migrant (pres/abs)	Kenya	0.47	0.50	0.0	1
Remittance from specific migrant (pres/abs)	Nigeria	0.48	0.50	0.0	1
Remittance from specific migrant (pres/abs)	Senegal	0.53	0.50	0.0	1

Remittance from specific migrant (pres/abs)	Uganda	0.26	0.44	0.0	1

Table S1c

Categorical descriptive statistics by country, **one observation per remittance sender** (n = 16,898). Number of **observations** by country: Burkina (n = 3716), Kenya (n = 3073), Nigeria (n = 2334), Senegal (n = 2866), South Africa (n = 2107), and Uganda (n = 2802). Wealth index is a standardized measure of wealth created country by country; here we present descriptive statistics for wealth index by country, unlike in the main text, where we report wealth standardized at the sample level to enhance comparability across countries.

Variable	country	Category	N	Percent
Migrant current location	Burkina Faso	international	1,510	40.6
Migrant current location	Burkina Faso	national	1,620	43.6
Migrant current location	Burkina Faso		586	15.8
Migrant current location	Kenya	international	1,047	34.1
Migrant current location	Kenya	national	1,416	46.1
Migrant current location	Kenya		610	19.9
Migrant current location	Nigeria	international	766	17.9
Migrant current location	Nigeria	national	2,874	67.2
Migrant current location	Nigeria		636	14.9
Migrant current location	Senegal	international	1,233	43.0
Migrant current location	Senegal	national	1,001	34.9
Migrant current location	Senegal		632	22.1
Migrant current location	South Africa	international	80	3.8

Migrant current location	South Africa	national	389	18.5
Migrant current location	South Africa		1,638	77.7
Migrant current location	Uganda	international	403	14.4
Migrant current location	Uganda	national	1,455	51.9
Migrant current location	Uganda		944	33.7
Migrant from household or not	Burkina Faso	hh	2,160	58.1
Migrant from household or not	Burkina Faso	non-hh	995	26.8
Migrant from household or not	Burkina Faso		561	15.1
Migrant from household or not	Kenya	hh	2,213	72.0
Migrant from household or not	Kenya	non-hh	277	9.0
Migrant from household or not	Kenya		583	19.0
Migrant from household or not	Nigeria	hh	3,020	70.6
Migrant from household or not	Nigeria	non-hh	625	14.6
Migrant from household or not	Nigeria		631	14.8
Migrant from household or not	Senegal	hh	2,037	71.1
Migrant from household or not	Senegal	non-hh	197	6.9
Migrant from household or not	Senegal		632	22.1

Migrant from household or not	South Africa	hh	351	16.7
Migrant from household or not	South Africa	non-hh	120	5.7
Migrant from household or not	South Africa		1,636	77.6
Migrant from household or not	Uganda	hh	1,642	58.6
Migrant from household or not	Uganda	non-hh	216	7.7
Migrant from household or not	Uganda		944	33.7

Table S2

Descriptive statistics **for 371 households above 3 standard deviations of spatial extent**, **one observation per household**; all are in Nigeria.

Variable	Mean	SD	Min	Max
Any remittance (pres/abs)	0.65	0.48	0.00	1.00
Autocorrelation	-0.02	0.00	-0.02	-0.02
Dist. to pop. center	0.71	0.71	0.01	2.76
Frequency	0.20	0.00	0.20	0.20
Household size	5.01	2.70	1.00	19.00
Mean NDVI	0.23	0.03	0.20	0.29
Number of migrants	1.88	2.04	0.00	15.00
Severity	0.50	0.14	0.23	0.69
Spatial extent	1,062,984.62	0.00	1,062,984.62	1,062,984.62
Wealth index (std.)	-0.17	0.93	-2.38	1.47

Figure S3

3D scatterplot (from two angles) of standardized observations for severity, frequency, and spatial extent, colored by country. For an interactive version of this plot, see https://github.com/annethro/remittances

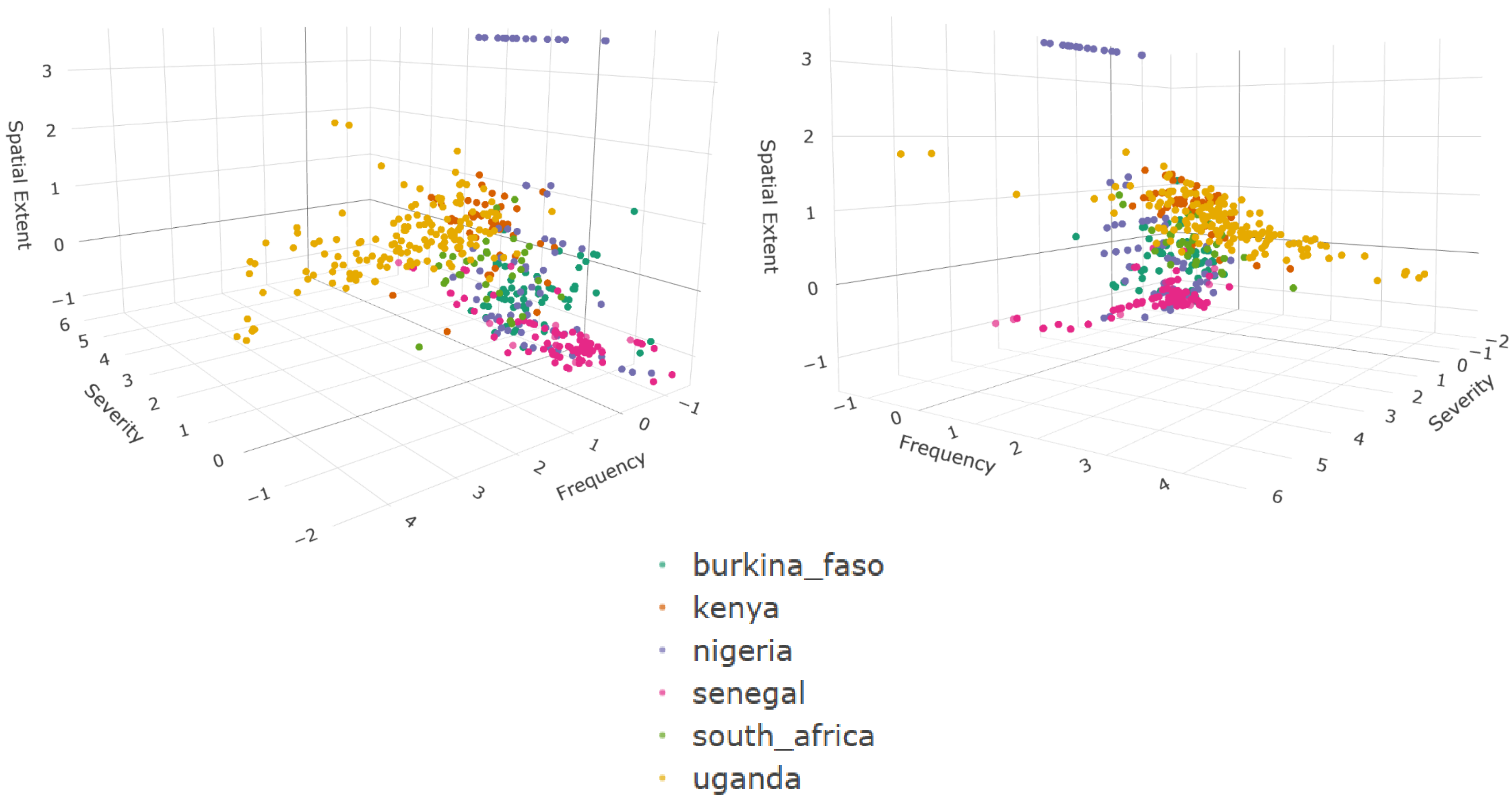
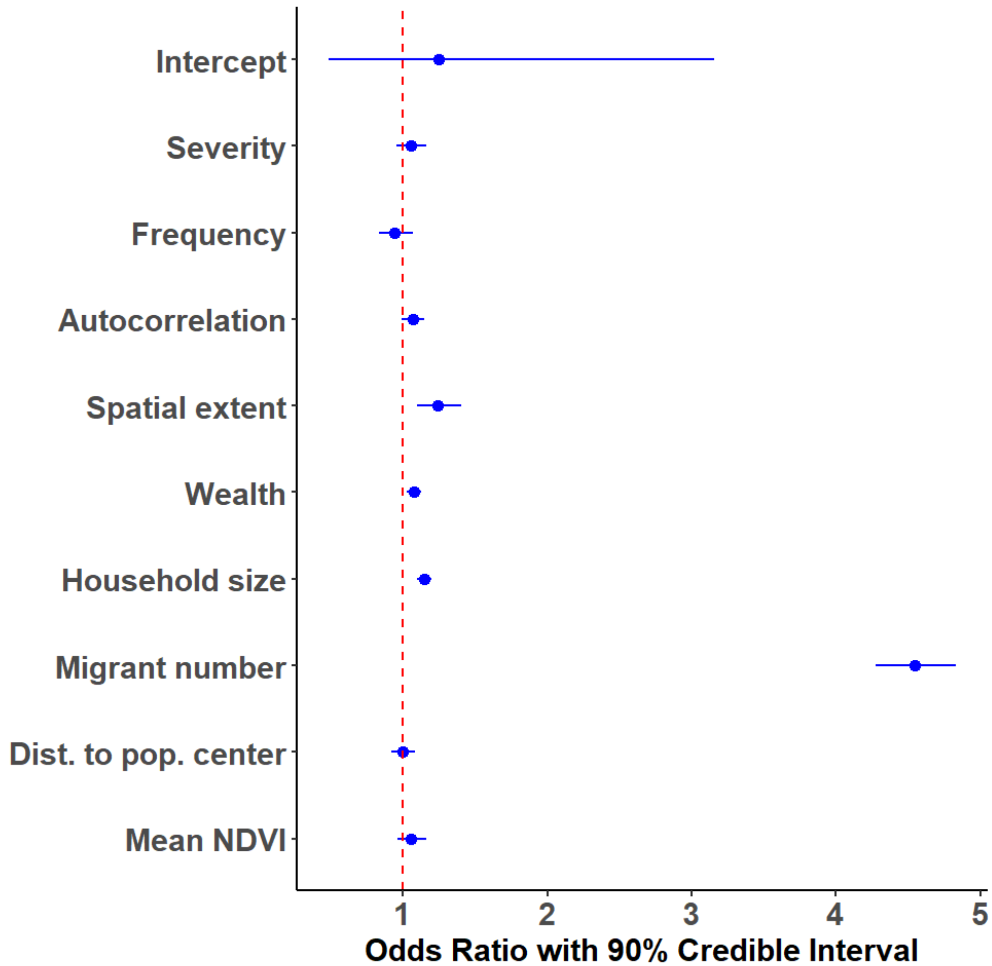


Figure S4

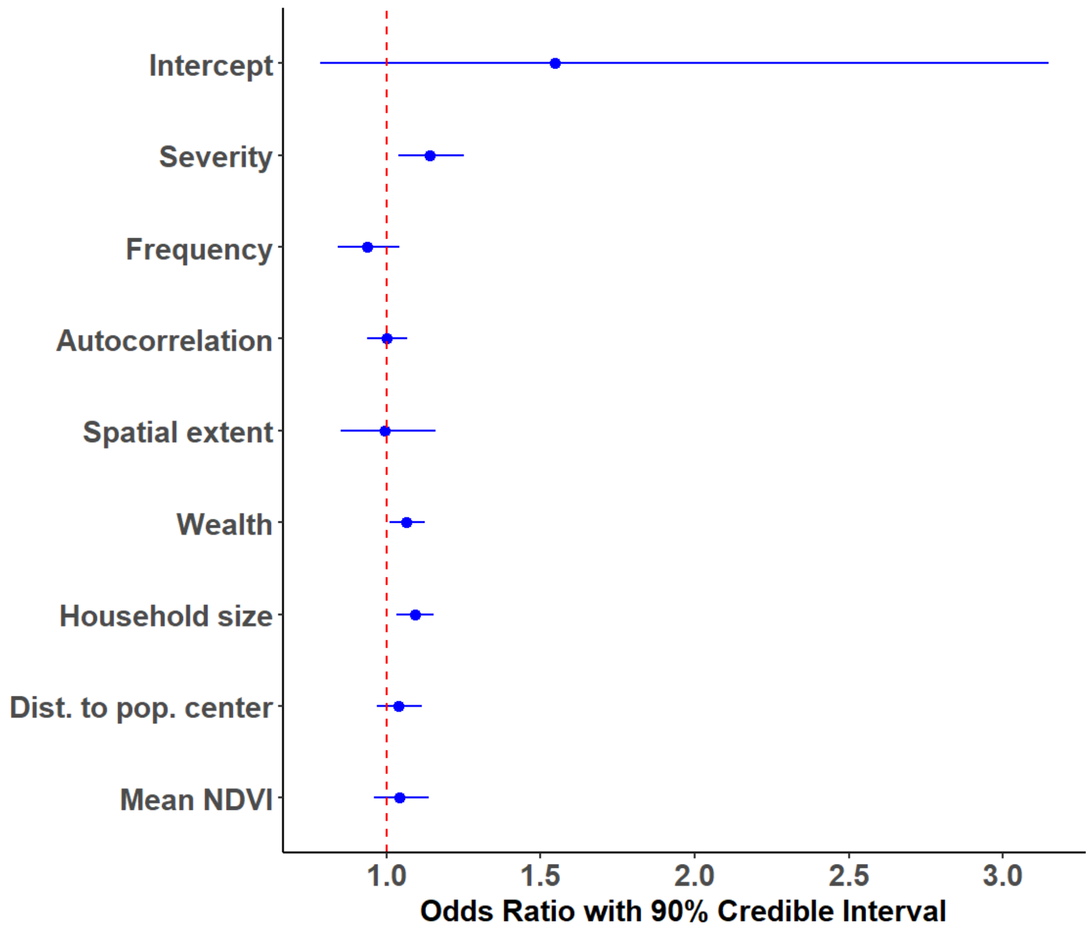
Results from our Bayesian mixed-effect, logistic model, **using a drought threshold of -1.5 standard deviations of the SPEI**, reported as odds ratios with 90% credible intervals; model otherwise identical to the main model reported in the article text. All variables were standardized prior to model fitting.



Bayesian R2 = 0.39. Random intercepts: interview date (SD = 0.54), country (SD = 1.35), and census tract (SD = 1.07).

Figure S5

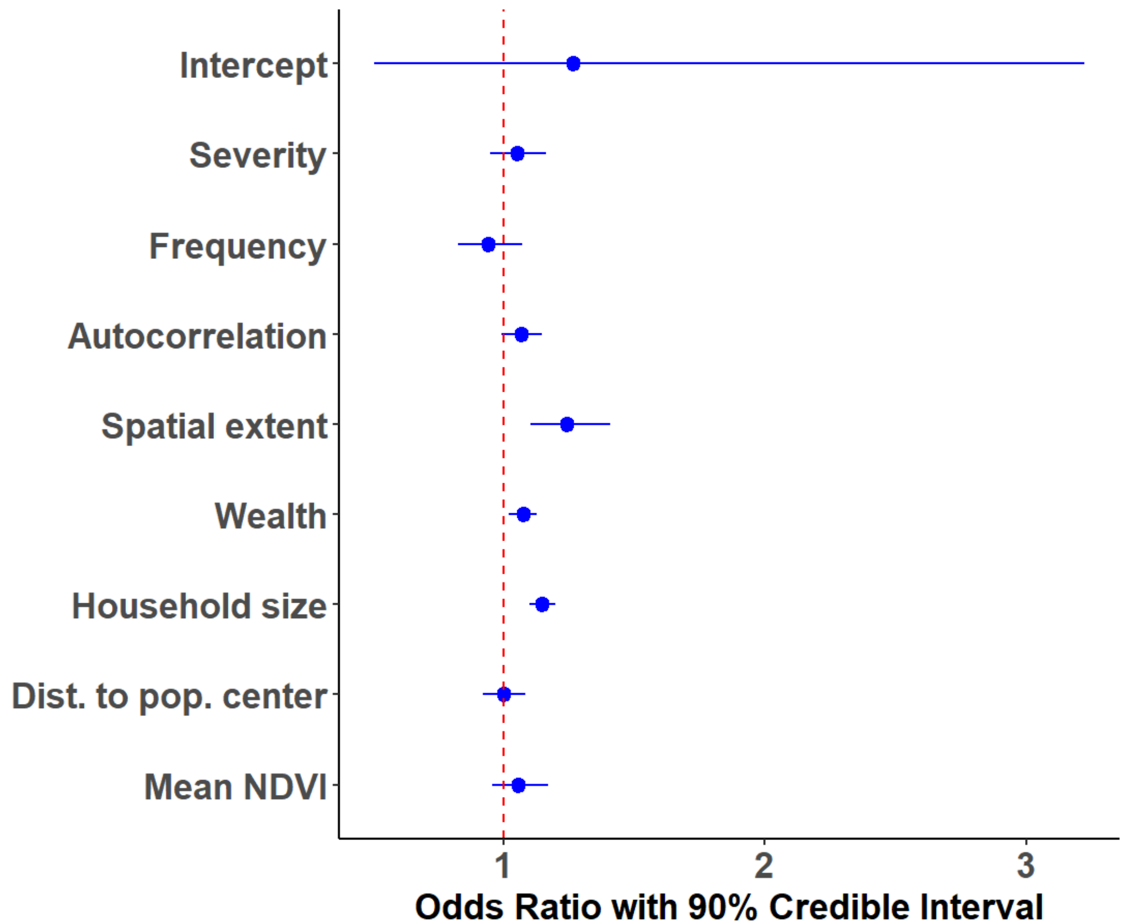
Results from our Bayesian mixed-effect, logistic model, **excluding n=371 households with experience of > 3 SD spatial extent and n=41 households with experience of > 3 SD severity – outliers identified in S6 that could influence model fit**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. The estimate for migrant number is not plotted as it made other estimates difficult to see (OR = 10.13, 90% CI = 9.07-11.34). All variables were standardized prior to model fitting.



Bayesian R2 = 0.33. Random intercepts: interview date (SD = 0.09), country (SD = 0.85), and census tract (SD = 0.77).

Figure S6

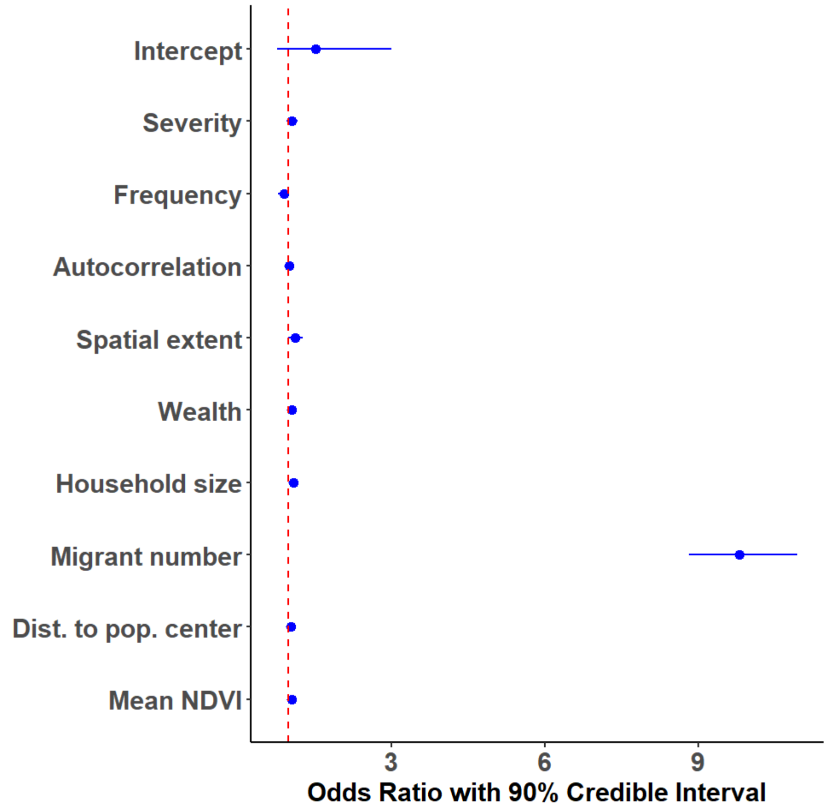
Results from our Bayesian mixed-effect, logistic model, **using a drought threshold of -1.5 standard deviations of the SPEI and excluding n=371 households with experience of > 3 SD spatial extent and n=41 households with experience of > 3 SD severity – outliers identified in S6 that could influence model fit**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. The estimate for migrant number is not plotted as it made other estimates difficult to see (OR = 4.55, 90% CI = 4.27-4.84). All variables were standardized prior to model fitting.



Bayesian R2 = 0.39. Random intercepts: interview date (SD = 0.55), country (SD = 1.34), and census tract (SD = 1.07).

Figure S7

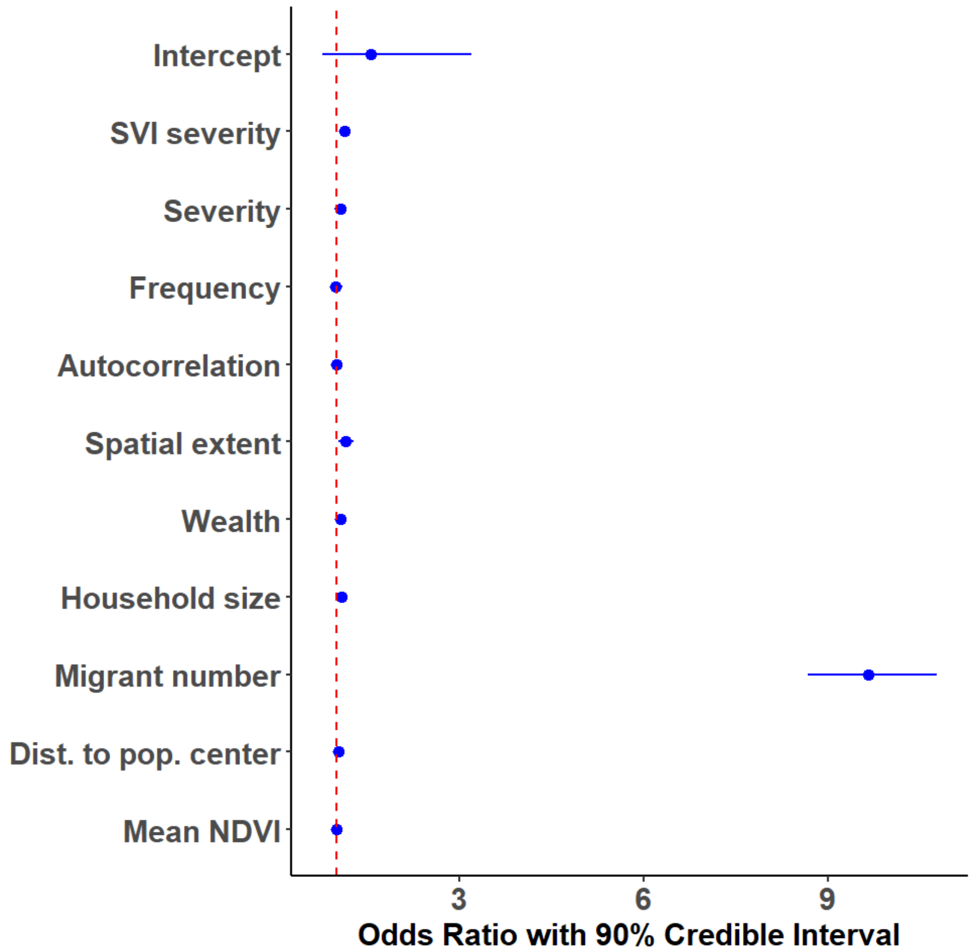
Results from our Bayesian mixed-effect, logistic model, **using a time window of 2000-2009**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. All variables were standardized prior to model fitting.



Bayesian R2 = 0.34. Random intercepts: interview date (SD = 0.10), country (SD = 1.04), and census tract (SD = 0.74).

Figure S8

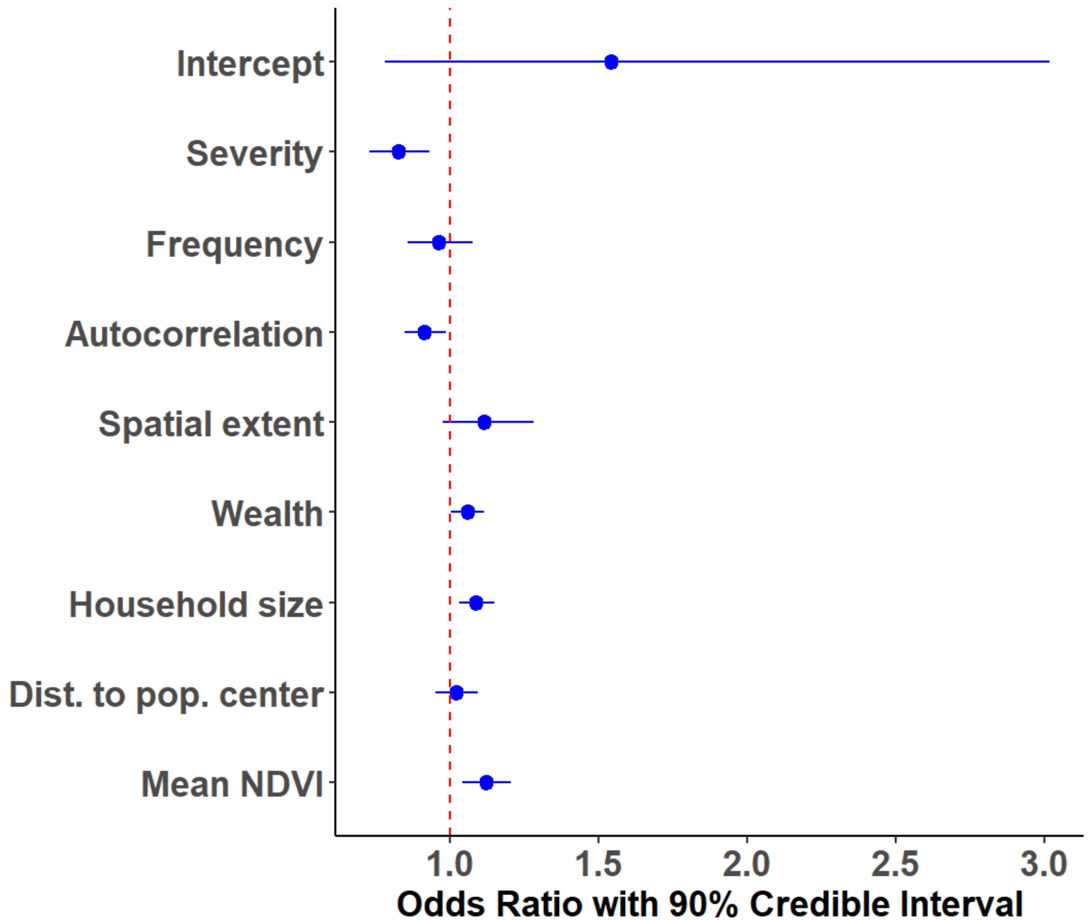
Results from our Bayesian mixed-effect, logistic model, **including standardized vegetarian index (SVI) severity**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. All variables were standardized prior to model fitting.



Bayesian R2 = 0.34. Random intercepts: interview date (SD = 0.11), country (SD = 1.05), and census tract (SD = 0.73).

Figure S9

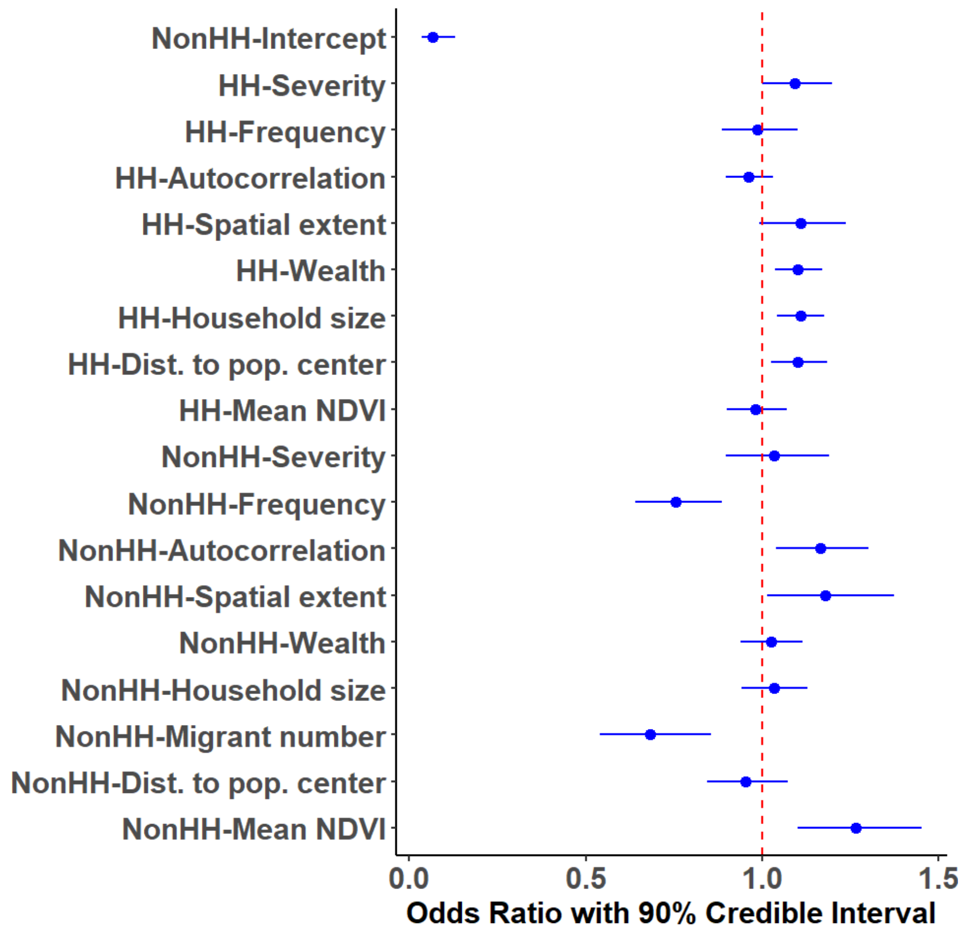
Results from our Bayesian mixed-effect, logistic model, **using a 12-month SPEI**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. The estimate for migrant number is not plotted as it made other estimates difficult to see (OR = 9.85, 90% CI = 8.84-10.95). All variables were standardized prior to model fitting.



Bayesian R2 = 0.34. Random intercepts: interview date (SD = 0.10), country (SD = 0.97), and census tract (SD = 0.74).

Figure S10

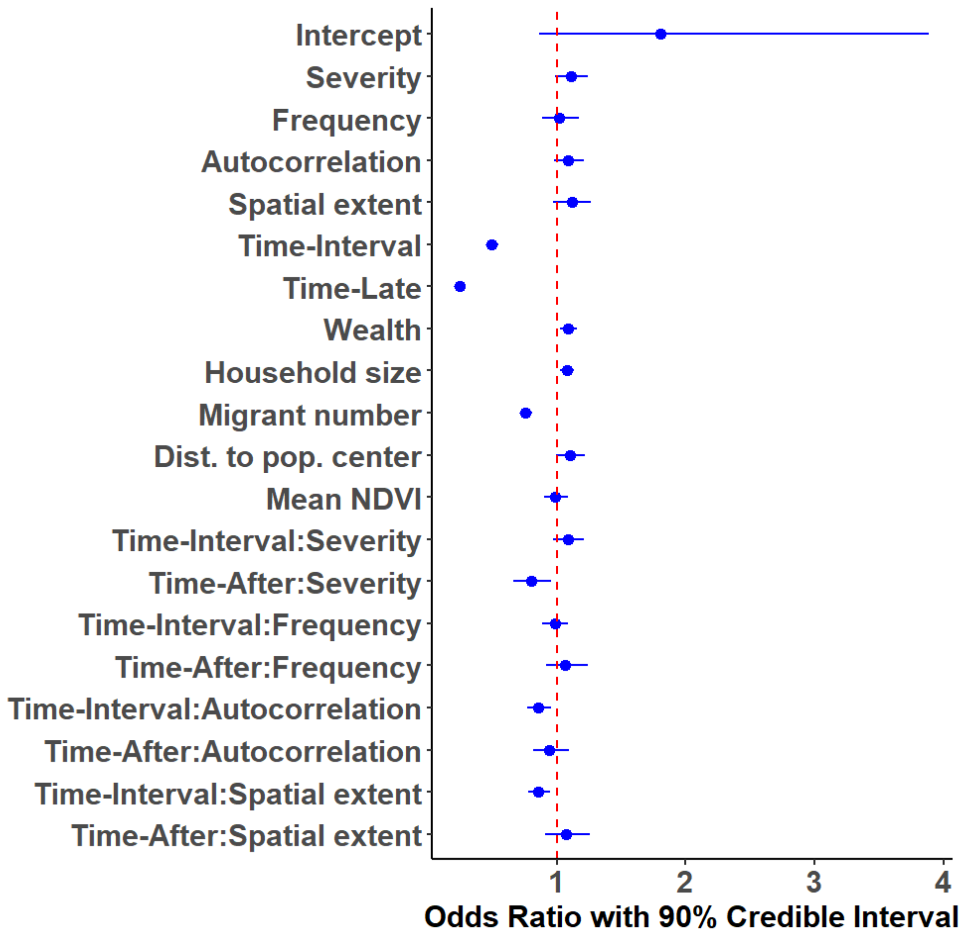
Results from our Bayesian mixed-effect, **categorical** model. **Each row in the dataset is a migrant instead of a household, and our outcome is whether or not each migrant sent a remittance in the last 12 months. We estimate two sets of model parameters – one for household migrants and one for non-household migrants.** Results are reported as odds ratios with 90% credible intervals. All variables were standardized prior to model fitting.



Bayesian R2 cannot be measured for categorical models like this one. Random intercepts: household migrant interview date (SD = 0.13) and non-household migrant interview date (SD = 0.12); household country (SD = 1.13) and non-household country (SD = 0.91); household census tract (SD = 0.77) and non-household census tract (SD = 1.04); and household migrant house (SD = 0.08) and non-household migrant house (SD = 0.23).

Figure S11

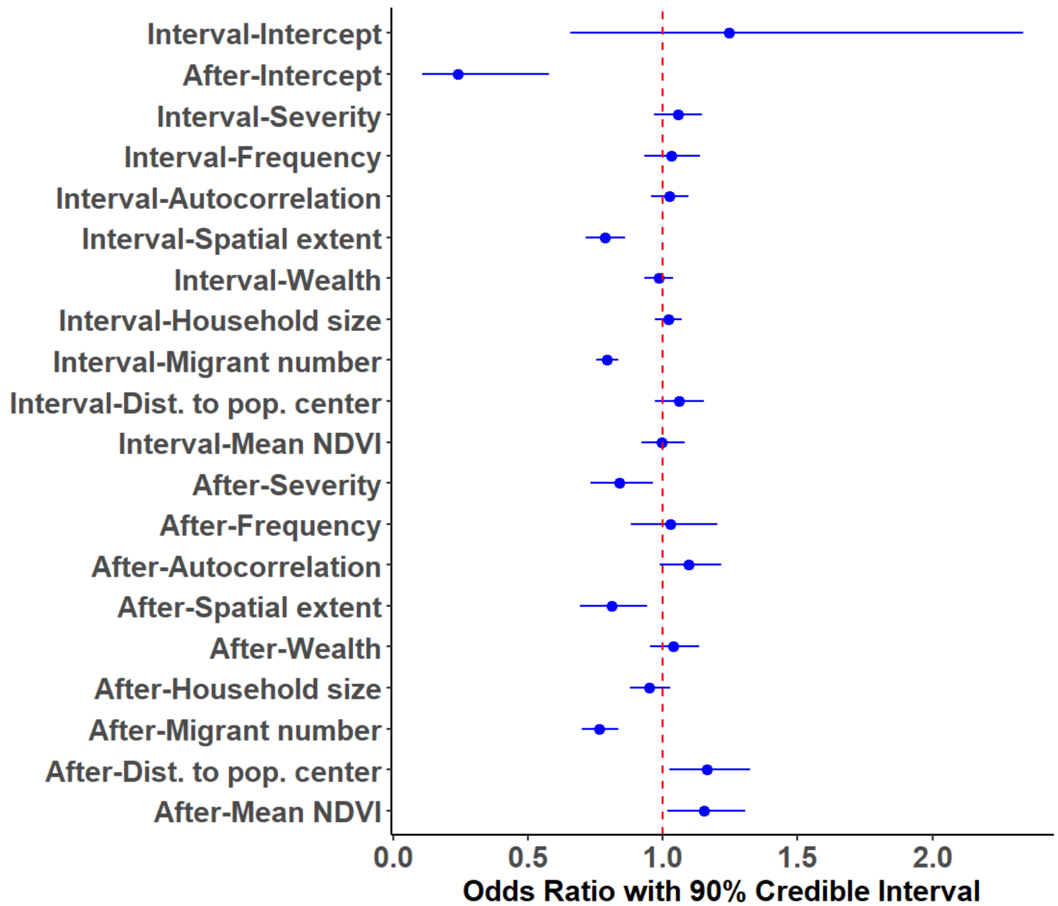
Results from our Bayesian mixed-effect, logistic model. **Each row in the dataset is a migrant instead of a household, and our outcome is whether or not each migrant sent a remittance in the last 12 months. We interact when the migrant moved** – before the five-year interval (held at baseline), 1-4 years prior to the interview (Time-Interval), and in the last 12 months before the interview (Time-After) with the four drought characteristics. Results are reported as odds ratios with 90% credible intervals. All variables were standardized prior to model fitting.



Bayesian R2 = 0.27. Random intercepts: interview date (SD = 0.22), country (SD = 0.98), census tract (SD = 0.85), and house (SD = 0.83).

Figure S12

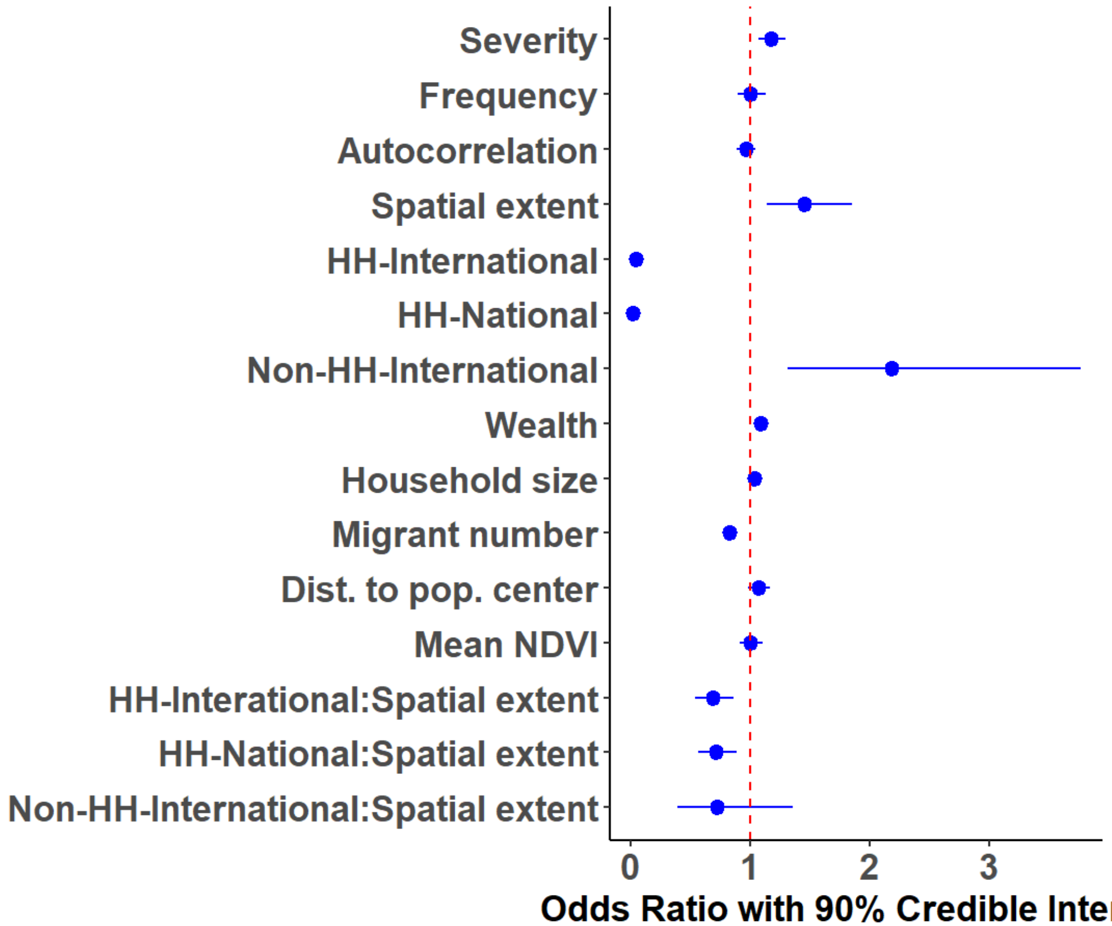
Results from our Bayesian mixed-effect, **categorical** model. **Each row in the dataset is a migrant instead of a household, and our outcome is the timing of their last move**: before the five-year interval (held at baseline), 1-4 years prior to the interview (Time-Interval), and in the last 12 months before the interview (Time-After), thus the two sets of estimates. Results are reported as odds ratios with 90% credible intervals. All variables were standardized prior to model fitting.



Bayesian R2 cannot be measured for categorical models like this one. Random intercepts: interval interview date (SD = 0.13), after interview date (SD = 0.19); interval country (SD = 0.83), after country (SD = 1.10), interval census tract (SD = 0.64) and after census tract (SD = 1.07), interval house (SD = 0.61) and after house (SD = 0.87).

Figure S13

Results from our Bayesian mixed-effect, logistic model, **including an interaction between spatial extent and an indicator – whether a migrant is a household or non-household member, and the location of that migrant (national or international).** Results are reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. All variables were standardized prior to model fitting.



Bayesian R2 = 0.34. Random intercepts: interview date (SD = 0.24), country (SD = 0.90), census tract (SD = 0.85), and house (SD = 0.81).

Figure S14

Two-way interactions between spatial extent and the likelihood of a migrant sending a remittance based on whether they are a household member living nationally vs internationally or a non-household member living nationally or internationally. For model estimates from this model, see Figure S10.

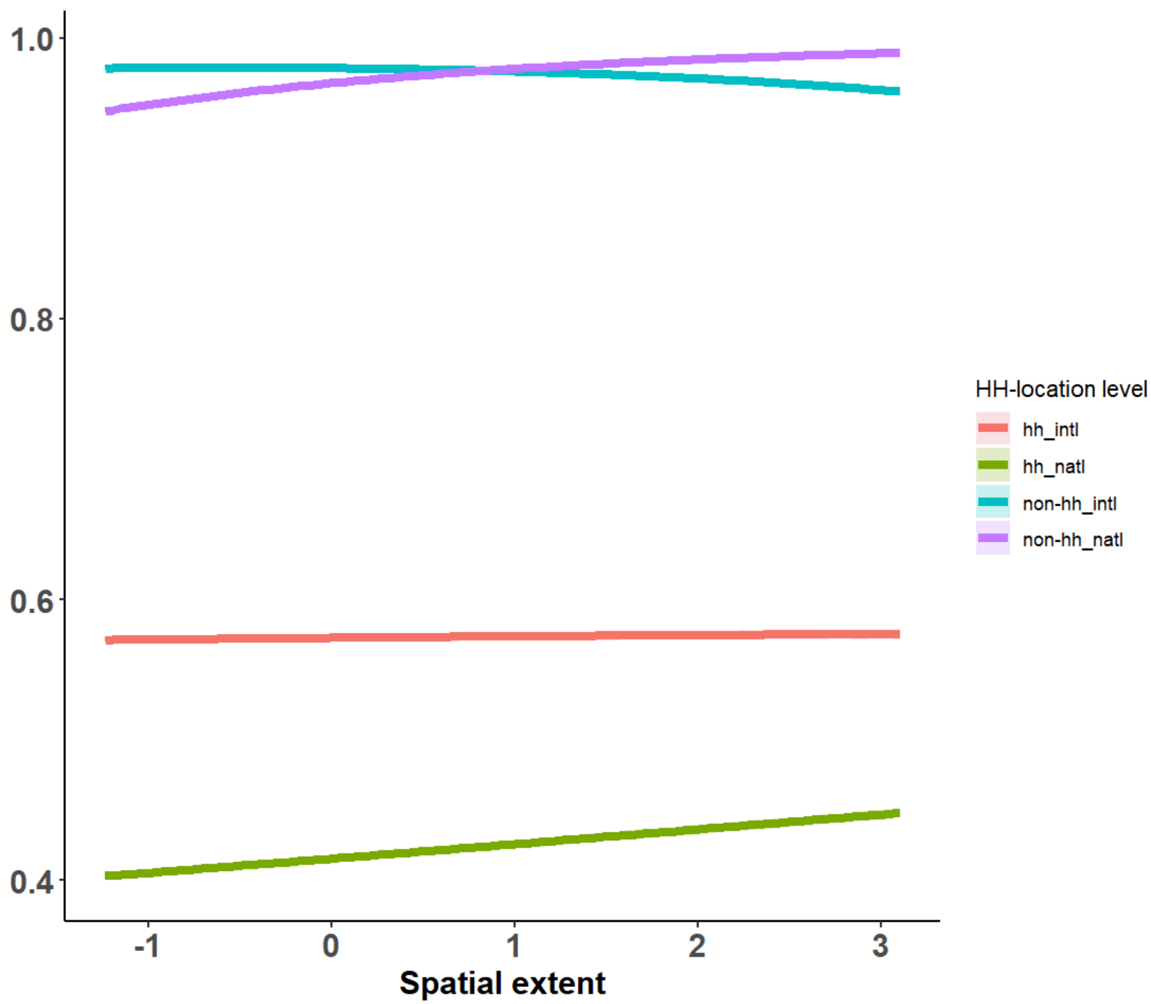
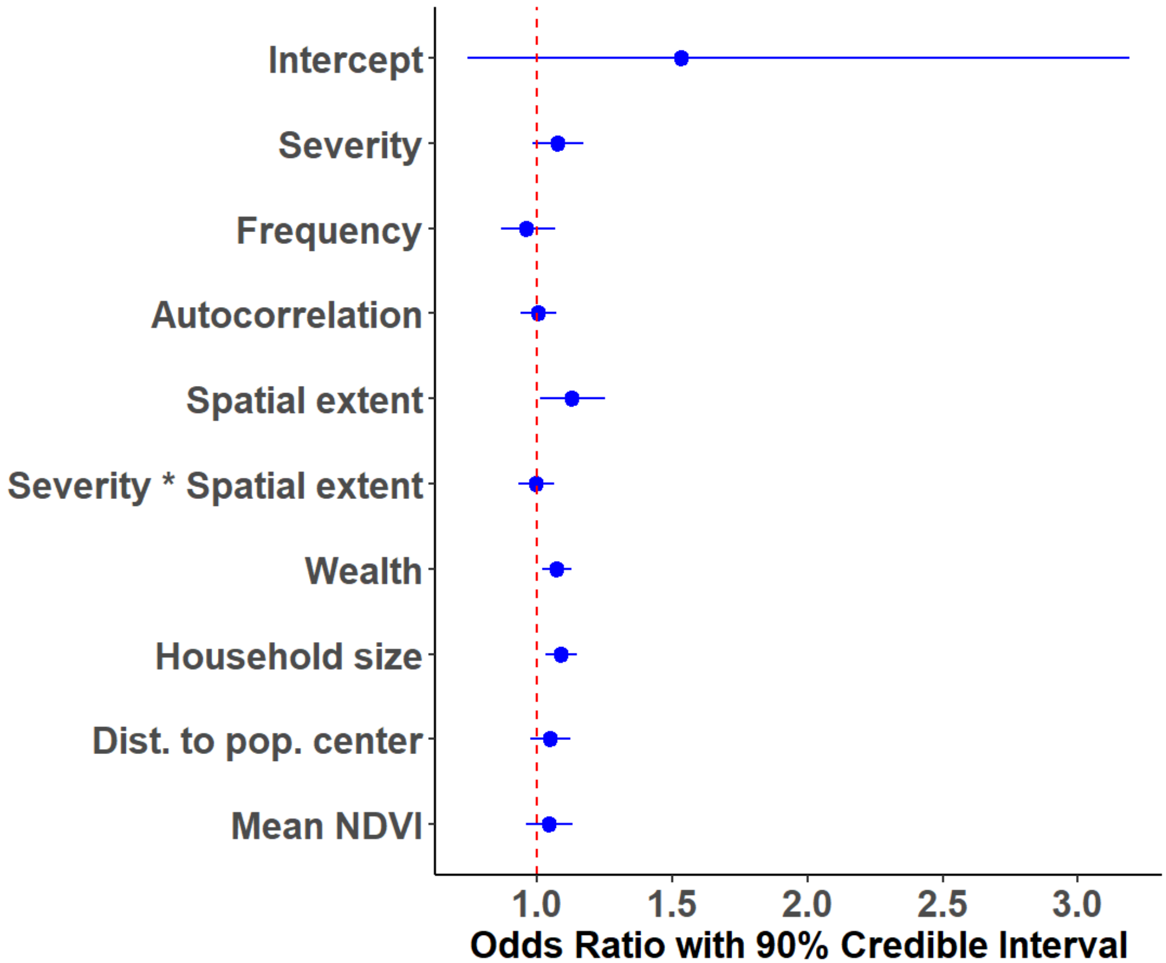


Figure S15

Results from our Bayesian mixed-effect, logistic model, **including an interaction between severity and spatial extent**, reported as odds ratios with 90% credible intervals; model was otherwise identical to the main model reported in the article text. The estimate for migrant number is not plotted as it made other estimates difficult to see (OR = 9.79, 90% CI = 8.82-10.89). All variables were standardized prior to model fitting.



Bayesian R2 = 0.34. Random intercepts: interview date (SD = 0.11), country (SD = 1.06), and census tract (SD = 0.74).