Does exposure to drought and floods predict long-distance social relationships in humans?

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1. INTRODUCTION

A likely adaptation to a high-risk foraging ecology, humans show flexible interest in long-distance social relationships – greater interest than observed among our closest relatives, for example (Pisor & Surbeck, 2019). In humans, long-distance social relationships can be sources of trade as well as reciprocal access to food, land, and places to sleep (Pisor & Surbeck, 2019). Building long-distance social relationships is just one of a number of flexible behavioral adaptations humans can use to manage risk however, including diet diversification, storage, savings for market-integrated or -integrating peoples, and within-community cooperative relationships (Agrawal, 2010; Halstead & O'Shea, 1982, 1989; Spielmann, 1986; Thornton & Manasfi, 2011). Based on our characterizations of the risks posed by different environmental hazards (Pisor & Jones, n.d.), we expect that if individuals have experienced floods and droughts in the past, they will have behavioral adaptations to manage the risks posed by those hazards. However, if hazards are chronic (for example, of long duration) or if they are more temporally autocorrelated (that is, tend to occur closer together in time), sources of risk management on the local scale – including storage or savings, switching to less-preferred foods, and within-community sharing – are likely to be depleted, favoring investment in alternative adaptations such as long-distance social relationships (Minnis, 1985; Pisor & Jones, n.d.). However, long-distance social relationships can be costly to maintain: for example, visitation can require long travel times (Fitzhugh, Phillips, & Gjesfjeld, 2011). Because of these costs, we should only expect individuals to invest in long-distance relationships when they anticipate future need; if hazards are patterned, rather than rare shocks, individuals will be more likely to invest in long-distance relationships (Minnis, 1985; Pisor & Surbeck, 2019).

In the present study, we investigate whether exposure to unusually-low levels of precipitation (that is, droughts) and unusually-high levels of precipitation (what we call "excess precipitation," related to flooding, high water levels, and landslides) predicts investment in long-distance social relationships. Specifically, however, we hypothesize that it is not the presence or absence of exposure to hazards like droughts and excess precipitation that will predict long-distance relationships, but specifically whether exposure is (1) chronic, (2) temporally autocorrelated, or (3) otherwise patterned (as opposed to anomalous). To assess whether these effects are specific to long-distance relationships or apply to social relationships in general, we also explore whether these same features of precipitation exposure impact the formation of same-community relationships. To investigate the predictions that emerge from these hypotheses, we draw on data AP collected among Bolivian horticulturalists (slash-and-burn farmers) about their migration histories, within-community relationships, and between-community relationships. The two collaborating communities live in a river valley in the La Paz Department of Bolivia. We combine these data with Standard Precipitation Index data from the National Center for Atmospheric Research (NCAR; (*Standardardized Precipitation Index (SPI) for global land surface (1949-2012)*, 2013)) to estimate participant exposure to excess precipitation and drought across their lifetimes.

2. HYPOTHESES, PREDICTIONS, EXPLORATORY ANALYSES, AND ANTICIPATED THIRD VARIABLES

For a visualization of planned models by combinations of predictors and outcomes, see Table 1.

H1: Adults who have experienced more chronic drought (or excess precipitation) during their lifetimes will be more likely to report having *long-distance relationships* than those who have less chronic exposure to drought (or excess precipitation).

- P1: Bolivian horticulturalists who have, on average, experienced longer intervals of drought (or excess precipitation) will report a greater number of friendships with people who live outside their local community.

Alternative H1: Adults who have experienced chronic drought (or excess precipitation) during their lifetimes will be more likely to report having *same-community relationships* than those who have experienced less frequent droughts (or excess precipitation).

- Alternative P1: Bolivian horticulturalists who have, on average, experienced longer intervals of drought (or excess precipitation) will be more likely to report a reciprocity-based relationship with another household in their local community.

H2: Adults who have experienced more temporal autocorrelation between droughts and excess precipitation will be more likely to report having long-distance relationships.

- P2: Bolivian horticulturalists who have experienced less time on average between intervals of drought and excess precipitation will report a greater number of friendships with people who live outside their local community.

Alternative H2: Adults who have experienced a higher degree of temporal autocorrelation between droughts and excess precipitation will be more likely to report having same-community relationships.

- Alternative P2: Bolivian horticulturalists who have experienced less time on average between intervals of drought and excess precipitation will be more likely to report a reciprocity-based relationship with another household in their local community.

H3: Adults who have repeatedly experienced droughts (or excess precipitation) will be more likely to report having long-distance relationships.

- P3: Bolivian horticulturalists who have experienced a greater number of individual months of drought (or excess precipitation) – that is, months 1 standard deviation below (or above) local average precipitation – scaled by the months for which we have data on their precipitation exposure, will report a greater number of friendships with people who live outside their local community.

Alternative H3: Adults who have repeatedly experienced droughts (or excess precipitation) will be more likely to report having same-community relationships.

- Alternative P3: Bolivian horticulturalists who have experienced a greater number of months of drought (or excess precipitation) – that is, months 1 standard deviation below (or above) local average precipitation – scaled by the months for which we have data on their precipitation exposure, will be more likely to report a reciprocity-based relationship with another household in their local community.

3. DATA COLLECTION

In March-June 2017, members of two horticulturalists communities in the La Paz Department of Bolivia, were interviewed by AP about their migration histories, friends who they do not see in person often, and whether there is a member of their community with whom they have a reciprocal cooperative relationship. A total of n=119 individuals participated. Given variable literacy across participants, but familiarity with signing documents, consent forms were read aloud and participants provided written (that is, signed) consent. All field protocols were approved by the Max Planck Institute for Evolutionary

Anthropology Department of Human Behavior, Ecology, and Culture, and declared exempt from additional IRB oversight.

4. PREPARATION OF PREDICTORS AND OUTCOMES

4.1 Drought and excess precipitation exposure

4.1.1 Precipitation data. Precipitation accumulation data were downloaded from the NCAR Computational and Information Systems Laboratory (*Standardardized Precipitation Index (SPI) for global land surface (1949-2012)*, 2013). Data were available from January 1, 1949 through December 31, 2012 and are reported for one latitude by one longitude cells globally. Daily precipitation accumulation tends to follow a gamma distribution (Martinez-Villalobos & Neelin, 2019). However, common practice in meteorological science is to average daily precipitation accumulation by month or by longer periods, up to 48 months in length, and then normalize these gamma-distributed data into a standard normal distribution (Orlowsky & Seneviratne, 2013). This approximation is appropriate as long as the shape parameter is large enough, which it usually is for precipitation data. The resulting index is called the Standardized Precipitation Index (SPI), a moving average calculated over intervals of anywhere from three months to 48 months and reported on the midpoint of that window (e.g., the SPI for a three-month window including January, February, and March would be reported for February; (McKee, Doesken, & Kliest, 1993)). We focus on the shortest of these intervals, three months, because of our focus on the impact of precipitation on human livelihoods (Svoboda, Hayes, & Wood, 2012): for the two communities in Bolivia, even one month of high precipitation can cause the failure of crucial cash crops, including papaya, cacao, and yuca. Per common practice, when there is an interval of below-average precipitation and the SPI for at least one month during that interval reaches -1 SD or lower, the interval from when precipitation goes negative (that is, falls below the average) and then returns to average or positive is considered the length of the drought; the opposite is true (i.e., at least one month of 1 SD or higher) to estimate the length of an interval of excess precipitation (McKee et al., 1993).

4.1.1.1 Limitations. As we noted, gamma-distributed data can be converted to a normal distribution without loss of information if the shape parameter is large enough. In particularly arid environments, data can be too zero-inflated to be approximated by a gamma distribution (Mishra & Singh, 2010). However, only one department in our data set -- Tarapacá, in Chile -- has many zero values for precipitation, and only two participants are coded as having lived in Tarapacá. As such, the potential effects of an inappropriate conversion of gamma to standardized normal in the case of Tarapacá is unlikely to affect our results.

The NCAR dataset did not include data from before 1949. (We attempted to remedy this problem with raw data of daily weather station precipitation data from NOAA, however there are few data available for Bolivian stations before the 1980s.) As such, we are unable to account for participants' exposure to precipitation if they were born before 1949; this affects a total of three participants. The NCAR dataset also did not include data from after 2012, affecting all participants in the sample. When we scale by months of exposure for testing H3, we thus scale only by the years or months of the participant's life for which precipitation data were available.

If an interval includes an SPI of -1 SD or smaller, the entire period is coded as a period of drought (McKee et al., 1993). The same practice holds for periods of excess precipitation (that is, intervals containing an SPI of +1 SD or larger). However, this assumption is not appropriate for evaluating H3 – whether an individual experiences a drought or excess precipitation as a rare shock or something patterned. For example, two 30 year-old individuals may have each experienced 20 months of -1 SD or lower precipitation, but those months might be distributed differently across different intervals of drought:

perhaps Individual A has experienced four intervals of drought, each with five months of -1 SD precipitation, but Individual B has experienced two intervals of drought, each with 10 months of -1 SD precipitation. By the McKee et al. (1993) definition, Individual A has experienced more droughts than Individual B, but both have equal experience with bad months – when production is likely to be impacted by low precipitation. As such, we evaluate H3 using total months of -1 SD or lower (or +1 SD or higher) precipitation experienced, rather than total intervals.

4.1.2 Migration data. Participants were asked to name the departments in which they had lived or to which they had traveled during their lives. Participants reported the ages at which they went to each location – including their age at each visit, if they went multiple times. Because data were collected as ages rather than dates, the finest-grained inference we can do in terms of when a participant lived in a place is if they lived there for an entire year, uninterrupted. A total of 55 (of n=121) participants reported living elsewhere for at least a year. For simplicity, we assume all participants were born on January 1 and that one year of residence is January 1 to December 31. For example, if a participant was born in 1980 and reported living in Santa Cruz for a year starting at age 22, we estimate that they lived in Santa Cruz from January 1, 2002 until December 31, 2002. Two participants reported living in one location for 1.5 years and 2.5 years, respectively; these values were rounded up to the nearest whole year.

4.1.2.1 Limitations. Participants who had lived outside the La Paz Department of Bolivia named the department in which they had lived. Participants who had lived abroad, usually while doing migrant labor, often named only the country in which they had lived. If they did mention the department in which they lived, or if we were able to infer it from other responses they gave, we assigned them to that department for the interval in question; if they did not mention the department, we drew on Bolivian migration data from the International Organization for Migration (IOM; *Organización Internacional para las Migraciones*) and AP's ethnographic data to assign participants to the department where they were most likely to have lived (e.g., Buenos Aires in Argentina, Tarapacá in Chile). Only nine individuals reported living outside of Bolivia, so these assignments affect few individuals in our sample.

To estimate the intervals during which participants lived in the La Paz Department, AP removed intervals during which participants reported living elsewhere; for all other intervals, they were considered La Paz residents. For example, if a 40 year-old participant was born in the La Paz Department but briefly moved to Chile from ages 24-25, they were recorded as living in the La Paz Department from 0-23, in Chile from ages 24-25, and in the La Paz Department from ages 26-40. Note that participants may have engaged in shorter-term migration the time they were coded as living in the La Paz Department: for example, a six-month stint in the Pando Department would not be captured.

4.1.3 Precipitation data per location. To estimate a participant's exposure to drought (or excess precipitation), we use a combination of the SPI data, their migration history, and shapefiles (Hijmans, n.d.) of the departments in Bolivia and in neighboring countries. SPI data obtained from NCAR (Section 4.1.1) are summarized in a grid of 1 longitude by 1 latitude cells; using shapefiles delimiting the boundaries of each department, we matched SPI data to the departments in which they fell. We then averaged the SPI across all cells inside a given department for a particular month (e.g., all SPIs inside the Santa Cruz Department in May 1990 were averaged). Participants were then said to experience this averaged SPI if they lived in a particular department during a particular month.

(H1) To estimate a participant's experience of chronic drought (or chronic excess precipitation), we took the mean length of the number of closed intervals during which the SPI they experienced fell below -1 SD (or above 1 SD). Note that per McKee et al. (1993), a closed interval for drought begins when precipitation falls below average, *if at some point during that below-average interval the SPI reaches -1 SD or below*, and ends when the SPI again reaches average or higher; the inverse is true for excess precipitation. If participants moved between departments during an interval of below-average or above-average precipitation, we continue that interval in the new location. For example, if a participant experienced an above-average interval with at least one +1 SD SPI value in the Pando Department and, during that interval, moved to the Oruro Department, if Oruro was likewise in an above-average interval, the interval continues for that participant until the SPI value in Oruro returns to average; if they moved to Oruro and Oruro was in an average or below-average interval, that closes the interval.

(H2) Temporal autocorrelation in precipitation is a latent variable that individuals experience as environmental risk. To estimate how much time a participant, and their risk-management adaptations, have had to recover between bouts of drought and excess precipitation, we first begin by calculating closed intervals of drought and excess precipitation as described for (H1), above. We then calculate time *not* spent in an interval of drought or excess precipitation – intervals of "normalcy" between droughts and excess precipitation. We take the average length of all these intervals to estimate a participant's experience of temporal autocorrelation of droughts and excess precipitation – the average latency in onset before the next event. Participants who have *shorter* inter-drought/excess precipitation intervals on average are experiencing more temporal autocorrelation between events.

(H3) To estimate a participant's patterned exposure to drought (or excess precipitation), we counted months of a participant's life during which the departmental SPI was at or below -1 SD (or was at or above +1 SD) by summing the binary indices described above and then divided by the total months of that participant's life for which we have precipitation data (1949-2012). Note that this does not follow the interval approach in (H1) (McKee et al., 1993): only the months that fall below -1 SD or above +1 SD are counted, not entire intervals that contain a month with at least -1 SD or +1 SD (see 4.1.1.1 for discussion). Participants who have lower values on this measure may be more likely to experience a drought (or excess precipitation) as a shock rather than something with predictable recurrence.

4.1.3.1 Limitations. There is within-department variation in rainfall that is masked when the SPI for a particular month is averaged at the department level. For example, the La Paz Department includes rainforest, cloud forest, and Andean plateaus, all with a very different precipitation profile. However, because AP asked only about department of residence, we do not have finer-grained data with which to assess participants' exposure to precipitation.

4.2 Long-distance relationships

Participants were asked to count their number of friends "who live elsewhere, whom they see only once in a while." AP then asked participants to identify where these friends live (inside of Bolivia, by community or city name, or outside of Bolivia, by country name) and whether they and their friends "help each other" or "do favors for each other." We parameterize number of long-distance relationships in two different ways. First, for our primary analyses, we consider the total number of individuals named in response to this question. Participants named between 0 and 9 people; however, as only 11 participants named four or more connections (cf. 16 named three, 27 named two), of which only one each named six, seven, or eight, we round those who named more than three to three. Second, as a robustness check, we consider only the friends with whom the participant reported some type of reciprocity. To avoid participant fatigue, AP asked for details only about the first four individuals named, such that the range of the predictor is 0-4; note, however, only seven participants listed more than 4 long-distance connections, so little data is lost via this constraint. For 49% of all named long-distance friends, participants reported that they and their friends did not help one another, sometimes clarifying that they only reciprocated friendship (*sólo amistad)*. This makes the parameter more comparable to that for same-community relationships, which explicitly referred to reciprocal relationships (Section 4.3). As with the first parameterization, we bin higher values to make the size of each "level" of friends more comparable; as only 21 participants named two or more reciprocity-based relationships, versus 40 for one and 58 for zero, we round those who named two or more relationships to two.

4.3 Same-community relationships

Participants were asked to report whether there were any other households in their community with whom they had reciprocal sharing relationships (i.e., households described as "doing favors for you and your household" or "who help you and your household"). If there was at least one household with whom they had a reciprocity-based relationship, they were asked to name the things the other household did for them and the relationship of that household to their household (e.g., neighbors, kin, friends). We parameterize the presence or absence of same-community relationships in two different ways. First, for our primary analyses, we code merely the presence or absence of a reciprocity-based relationship in the same community. Second, as a robustness check, we code reciprocity-based relationships as "present" only if the household named was not related to the participant by blood (that is, consanguineal kinship). The assumption behind this robustness check is that reciprocity is less expensive to maintain with consanguineal kin (Trivers, 1971), such that individuals may only build more expensive relationships – those with non-kin – when the net benefits to doing so are higher, that is, in response to increased drought or excess precipitation exposure. However, it is also important to note that individuals may selectively form close relationships with kin who provide them with more net benefits: they may intensify relationships with particular siblings or cousins in response to need (Pisor & Ross, n.d.). Further, individuals may build affinal (marriage-based) relationships to expand their access to cooperative partners (Chapais, 2008; Pisor & Surbeck, 2019); we thus include these among the more expensive relationships.

4.4 Relevant third variables

- People who have spent time in more places will have had more opportunities to make social connections. We count the number of departments in which a participant has cumulatively (that is, across their lifetime) spent a month or more and include that in the model as a control for such opportunities. Note that this count includes not only the places where they have lived a year or more, per the above migration data, but also places where they lived or worked for anywhere between one month and one year, or places to which they returned multiple times (e.g., to visit family or friends).
- People who are more outgoing may have more connections. We control for this by summing participant responses to two ordinal scales about how outgoing they are (adapted from the Newcastle Personality Assessor (Nettle, 2009)) and including this index in our models.
- People who have cellphones and/or vehicles will have an easier time maintaining long-distance relationships, as they can more easily connect with or visit their contacts. This is especially the case for participants who have access to smartphones: rural Bolivians rely on apps like WhatsApp and Facebook Messenger because they are inexpensive to use compared to phone calls and texts. While only eight participants lived in households with neither a cellphone nor smartphone, 52 lived in households with no smartphone; further, those with smartphones in their homes are not significantly likely to be older, a potential confound of this measure. Given the small number of individuals who are without any phone access, and given that smartphones were especially important to maintaining long-distance relationships in 2017, we control for household smartphone ownership (presence/absence), as well as vehicle ownership (presence/absence), in our models.
- Participants came from two different communities, each of which formed for different historical reasons: one fissioned from a long-standing mission community of Mosetén, a local indigenous group; the other was formed when indigenous Aymara from the Andes were voluntarily resettled by the government in the 1960s. Since the two communities were founded, members of other indigenous groups have joined both. While a first pass analysis (two-sample t-test) suggests no differences in number of friends named for the two communities, for example, they do differ in other respects: Mosetén community members are less likely to have lived abroad. We include community as a random effect to pool parameter estimates by community and account for unobserved variance.

- Age and sex are likely to affect number of long-distance relationships. Age may have effects for two reasons: (1) older individuals have had more cumulative time to form long-distance relationships; (2) younger individuals have grown up with greater access to roads than older individuals, including during years of their lives when they did not have dependents (which, according to participants and common sense, curb travel), implying potential cohort effects on the formation of long-distance relationships. Participant sex is also likely to affect the formation of long-distance social relationships for at least two reasons: (1) Total fertility averages four children in Bolivia, with higher fertility in rural than urban areas, and women are more likely to be responsible for dependent children. Cultural norms compound this, as childcare is generally considered to be women's work – though a mother's family may provide long-term care for her child while she engages in migrant labor or goes to college. (2) Men participate in mandatory military service, whereas women do not. Mandatory military service provides additional opportunities for long-distance relationship formation. Taken together, we include age and sex in our models as relevant third variables.
- We are neutral with respect to how far away non-local connections must live from the participant to buffer the risks posed by drought or excess precipitation. In another paper, we assess the theoretical role of degree of *spatial* autocorrelation for different resource shocks in the formation of long-distance relationships (Jones & Pisor in prep); here we focus on a simple measure of a participant's exposure to temporal autocorrelation.
- Note that we also do not have information on the occupations of long-distance connections. One might imagine that a long-distance connection involved in an industry other than agriculture might be better able to help buffer the effects of drought or excess precipitation, even if they live closer than rather than further away. This possibility should be studied in future work.

5. PLANNED ANALYSES

For a visualization of planned models by combinations of predictors and outcomes, see Table 1.

5.1 Average length of intervals of drought (or excess precipitation) exposure…

5.1.1 …predicting long-distance relationships (P1). To model the relationship between the length of the average interval of droughts (or excess precipitation) experienced by participants and their number of long-distance relationships, we use a sequential model with continuation parameterization implemented in R (R Core Team, 2017) with package `brms` (P. C. Bürkner, 2017). `brms` is a package that implements Bayesian models in Stan (Stan Development Team, 2015) using R.

Though a participant can have any non-negative number of long-distance relationships, in reality all but 27 had fewer than three; we accordingly binned all those with more than three friends as three. In other words, in this sample, only 4 different values for number of long-distance relationships was observed (0-3). It would not be defensible to model these data with a normal distribution: with so few values for long-distance relationships, normality assumptions would be inappropriate. Instead, we treat these data as ordinal – although unlike the model one might use for a scale outcome (commonly a cumulative link model), we model these data using a sequential model. Under a sequential model, participants cannot reach the next "level" of the variable in question without having reached the previous level first: one cannot have three long-distance relationships without first having had two (P.-C. Bürkner & Vuorre, 2019). We are interested in whether experience of drought or excess precipitation predicts attaining one long-distance relationship instead of zero, two instead of one, etc. – that is, continuing past each level to the next. As the probability of having each "level" of long-distance relationships is not expected to be particularly low (that is, close to zero) or particularly high (close to one), we use a logit link function (i.e., rather than an extreme-value link function; (P.-C. Bürkner & Vuorre, 2019)). At the outset, we will assume flexible spacing between thresholds for each level of long-distance relationships – for example, it may be more difficult for a participant with zero long-distance connections to build one, such that more drought exposure is required before they cross the threshold, relative to how difficult it is for a participant with two long-distance connections to build a third. However, assuming equidistance between thresholds involves estimating fewer parameters and thus increasing model power; as such, we will compare fits with flexible vs equidistant thresholds to see if the assumption of equidistance is warranted.

We will run two separate models, one with average length of drought intervals as the predictor of interest – included as a fixed effect – and one with average length of excess precipitation intervals as the predictor of interest. Community of residence will be included in the model as a random effect; the above-mentioned third variables (Section 4.4) will be included as fixed effects. Non-informative priors will be used for all variables.

5.1.1.1 Robustness check. For 49% of named friends living at a distance, participants reported that they and their friend were "just friends" – that is, they did not have a reciprocity-based cooperative relationship. To assess whether the relationship between drought (or excess precipitation) exposure applies only to reciprocity-based relationships and not all friendships, we will run this model a second time with reciprocity-based long-distance relationships as an outcome. We again bin higher levels for number of friends together, as only 21 participants had two or more reciprocity-based relationships; accordingly, reciprocity-based long-distance relationships take three levels: 0, 1, or 2. Again, we will use a sequential model with continuous parameterization, a logit link function, initial assumption of flexible thresholds (to be compared to equidistant thresholds), a community random effect, third variables as fixed effects, and non-informative priors. We will run this model two times, once with the average length of drought intervals as the (fixed effect) predictor of interest and once with average length of excess precipitation intervals as the (fixed effect) predictor of interest.

<u>5.1.2 …predicting same-community relationships (P1 alternate)</u>. To model the relationship between the average length of drought (or excess precipitation) to which a participant has been exposed and whether or not they have a same-community reciprocal relationship (a binary outcome), we use a binomial logistic regression again implemented in `brms`. Community of residence will be included in the model as a random effect; the above-mentioned third variables (Section 4.4) will be included as fixed effects. Non-informative priors will be used for all variables. We will run this model two times, once with average drought interval as the (fixed effect) predictor of interest and once with average excess precipitation interval as the (fixed effect) predictor of interest.

5.1.2.1 Robustness check. It may more costly to form reciprocity-based relationships with non-kin than with kin. Accordingly, to assess whether the relationship between drought (or excess precipitation) and same-community relationships is specific to the formation of relationships with non-kin, we will run this model a second time with the presence of reciprocity-based, same-community relationships with people other than consanguineal kin as the outcome. Again, we will run this model two times, once for drought and once for excess precipitation, using a binomial logistic regression with community as a random effect, third variables as fixed effects, and non-informative priors.

5.2 Average length of intervals between drought or excess precipitation events…

<u>5.2.1 …predicting long-distance relationships (P2)</u>. To capture participant experience of temporal autocorrelation between downsides, both droughts and excess precipitation, we use the average length of the intervals during which participants were experiencing neither a drought nor excess rainfall as a predictor. As there are not separate predictors for drought and excess precipitation in this case, only one model is needed. Per our explanation in Section 5.1.1, we utilize a sequential model with continuous parameterization with a logit link function, the initial assumption of flexible thresholds (to be compared

to equidistant thresholds), a community random effect, third variables as fixed effects, and non-informative priors. Our robustness check – using reciprocity-based long-distance relationships as the outcome – will take the same form as that described in 5.1.1.1. If you begin to lose track, recall that the different combinations of predictors and outcomes to be analyzed are visualized in Table 1.

5.2.2 …predicting same-community relationships (P2 alternate). Per our explanation in 5.1.2, we utilize a binomial logistic regression with the average length of the intervals during which a participant experienced neither drought nor excess rainfall as a predictor, with community as a random effect, third variables as fixed effects, and non-informative priors. Our robustness check – using non-consanguineal-kin, same-community relationships as the outcome – will take the same form as that described in 5.1.2.1.

5.3 Total months of drought (or excess precipitation) exposure…

5.3.1 …predicting long-distance relationships (P3). Per our explanation in Section 5.1.1, we utilize two sequential models with continuous parameterization – one with months of drought as a predictor, one with months of excess precipitation, both scaled for the number of months for which we have data for a participant – with a logit link function, initial assumption of flexible thresholds (to be compared to equidistant thresholds), a community random effect, third variables as fixed effects, and non-informative priors. Our robustness check – using reciprocity-based long-distance relationships as the outcome – will take the same form as that described in 5.1.1.1. If you begin to lose track, recall that the different combinations of predictors and outcomes to be analyzed are visualized in Table 1.

5.3.2 …predicting same-community relationships (P3 alternate). Per our explanation in 5.1.2, we utilize two binomial logistic regressions – one with months of drought as a predictor, one with months of excess precipitation, both scaled for the number of months for which we have data for a participant – with community as a random effect, third variables as fixed effects, and non-informative priors. Our robustness check – using non-consanguineal-kin, same-community relationships as the outcome – will take the same form as that described in 5.1.2.1.

5.4 Robustness checks

Descriptions of robustness checks are integrated into the text of Sections 4 and 5, and include assessing whether:

- Counts of long-distance relationships of any kind, or just long-distance relationships involving reciprocity, are predicted by chronic, temporally autocorrelated, and/or patterned exposure to drought or excess precipitation.
- The presence of same-community relationships of any kind, or just same-community relationships with non-consanguineal kin, are predicted by chronic, temporally autocorrelated, and/or patterned exposure to drought or excess precipitation.

Plotting of raw data suggest that outliers in the predictors may influence model fit for P1-P3. We will assess the influence of each data point on the outcome for each model; if individual points exert undue influence, we will re-run the model with influential points excluded as a robustness check.

Additionally, we use the package `mice` (Van Buuren & Groothuis-Oudshoorn, 2011) to impute values for one participant who did not complete the two questions about their extraversion. We will impute using predictive mean matching. As this is a third variable and has missing values for only one participant, imputation should have little effect on model results; however, we will inspect whether model fits change with the exclusion of this participant.

Table 1. Planned models across different combinations of predictors and outcomes.

		Outcome			
		Long-distance relationships	Reciprocity-based long-distance relationships	Same-community relationship	Same-community, non-kin relationship
Predictor	Intervals, drought	P1, model 1	P1, model 1, robustness	P1 alternate, model 1	P1 alternate, model 1, robustness
	Intervals, excess	P1, model 2	P1, model 2, robustness	P1 alternate, model 2	P1 alternate, model 2, robustness
	Autocorrelation, intervals without drought or excess	P2	P2, robustness	P2 alternate	P2 alternate, robustness
	Months, drought	P3, model 1	P3, model 1, robustness	P3 alternate, model 1	P3 alternate, model 1, robustness
	Months, excess	P3, model 2	P3, model 2, robustness	P3 alternate, model 2	P3 alternate, model 2, robustness

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