Supporting Information:

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

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Data, metadata, and code available at XXX

CONTENTS

1. ADDITIONAL LIMITATIONS OF THE 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). Some limitations of these data are discussed in the main text, Section 2.3; we confine our discussion here to additional, less crucial considerations.

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, called the Standard Precipitation Index (SPI) (Orlowsky & Seneviratne, 2013). This approximation is appropriate if the shape parameter is large enough, which it usually is for precipitation data. 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. We are thus 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.

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.

2. STATISTICAL MODELS

We pre-registered the analyses reported here on the Open Science Framework: https://osf.io/5pdn3/. AP pre-registered data collection too (https://osf.io/utwuf), although the goals of data collection differed from the hypotheses tested in this paper.

2.1 Weakly informative priors

We utilize very weakly informative priors for the models analyzed in this paper. Non-informative priors – commonly, flat priors with high lower and upper bounds – are usually an inappropriate choice for estimating parameter values: given that the null hypothesis is that predictors should not have any relationship with the outcome variable, the sampling process should focus on values closer to zero. To estimate the predictors of interest and third variables, we use the normal distribution with a mean of zero and a standard deviation of 10 as a prior. To estimate the random effect for community – reported as a standard deviation, which must be positive by definition – we use a half-Cauchy distribution with a location parameter of 0 and shape parameter of 2. For discussion of these choices of priors, see McElreath (2020).

2.2 Equidistant thresholds and unequal variance by community

As discussed in the main text, we found the assumption of equidistant thresholds (as opposed to flexible thresholds) warranted for all sequential model fits (Section 2.4.1). We compared model fits with flexible thresholds – that is, where the unique spacing between each pair of thresholds is estimated as part of the model fitting process – and models fits with equidistant thresholds – where the *identical* spacing between each pair of thresholds is estimated as part of the model fitting process – using leave-one-out cross-validation (Bürkner & Vuorre, 2019). By leaving out a single observation, refitting, and attempting to predict the value of the outcome for the omitted observation, and iterating that process, we can compare the ability of two different models to predict omitted observations. This comparison is done using the leave-one-out information criterion (LOOIC). LOOIC has advantages over other comparison techniques for Bayesian models, such as the Akaike Information Criterion (AIC), as it incorporates model priors and does not assume that the outcome variable is normally distributed; however, it is less sensitive to the choice of model priors than is the widely applicable information criterion (WAIC), making it a robust choice for our sequential models with weakly informative priors (Vehtari et al., 2017). As is standard practice for AIC, WAIC, and LOOIC, we compared the LOOIC of models with flexible and equidistant thresholds, selecting the model with the lowest LOOIC value.

In ordinal models, it is possible that there is unequal variance in the outcome by group, which can lead to inaccurate model estimates (Bürkner & Vuorre, 2019). Though the inclusion of a random effect for community estimates the amount of variation in the *observed* outcome due to community, it does not account for unequal variance in the latent variable that generated the different levels of friendship. Though this is more commonly a concern for cumulative models than for sequential models (Bürkner & Vuorre, 2019), we conducted exploratory analyses to examine whether unequal variance between communities was a concern. These models generated unrealistic model estimates with large credible intervals, indicating substantial uncertainty in the model fitting process. As such, do not report these models in the main text or Supporting Information; however, the code for running them can be found in our GitHub repository.

2.3 Outliers removed during the model fitting process

Exploratory data analysis indicated that outliers in the predictor variables could influence model fit for P1-P3. During the process of assessing different model fits, our first step was to fit a model in which we explicitly estimated the effect of the predictor of interest on the latent outcome; the latent outcome is called "discrimination," or "disc" (Bürkner & Vuorre, 2019). We then examined plots of the predicted values for the latent outcome, disc, to look for the potential influence of outliers; see our GitHub repository for the relevant code.

Outliers appeared to influence fit for the P1 drought model (n=2), as evidenced by both the plot of predicted values and, in the model fit including these participants, reduced estimated sample sizes for some variables and increased uncertainty in parameter estimates relative to the model fit without them. The model reported in the main text (Table 1) excludes these individuals. See our GitHub repository for reproducible code.

2.4 Procedures to reduce participant identifiability

We took two major precautions to reduce the identifiability of our participants. First, we converted all participant identification numbers (PIDs) to randomized identification numbers (RIDs) so that even the researchers cannot recognize these participants in publicly accessible data. Further, note that these RIDs are different across papers published using this data set; merging data sets from across publications by RID is not possible. Second, after completing the process of model fitting, we binned participant birth years into five-year bins (e.g., 1971 became 1970; 1999 became 1995) to further reduce participant identifiability. The binning of birth years did not alter model results.

Tables S1a-d. Descriptive statistics

(a) Ordinal variables that include zero in their range

Variable	Zero	One	Two	Three
Long-Distance	30	35	27	27
Reciprocal Long-Distance	58	40	21	
Same-Community	32	87		
Non-Con.* Kin Same-Community	103	16		
Smartphone	46	73		
Vehicle	84	35		

*Non-consanguineal kin

(b) Ordinal variables that include one in their range*

Variable	One	Two	Three	Four
Extraversion: Stranger*	60	16	42	
Extraversion: Conversation**	22	6	26	64

*This scale was coded as: "Never" = 1, "Sometimes" = 2, "Always" = 3.

**This scale was coded as: "Never" = 1, "Rarely" = 2, "Sometimes" = 3, "Always" = 4. For more information, see metadata available on GitHub.

(c) Nominal variables

Variable	One	Two
Community*	52	67
Sex**	67	52

*Community One is the Intercultural community, Community Two is the Mosetén community.

**Sex One is female, Sex Two is male.

(d) Continuous variables

Variable	Mean	SD
Number Dry Months	47.08	13.87
Number Wet Months	49.91	16.58
Mean Len. Drought	6.39	0.46
Mean Len. Excess P.*	5.80	0.82
Mean Len. No D. or E.P.*	6.75	0.93
Birth Year	1973.92	12.04
Depts. & Countries Visited	1.33	1.36

*P. = precipitation. D. = drought. E.P. = excess precipitation

Figure S1. Parameter estimates and 95% credible intervals for a robustness check of the five main models: treating *reciprocity-based long-distance relationships* as the outcome.

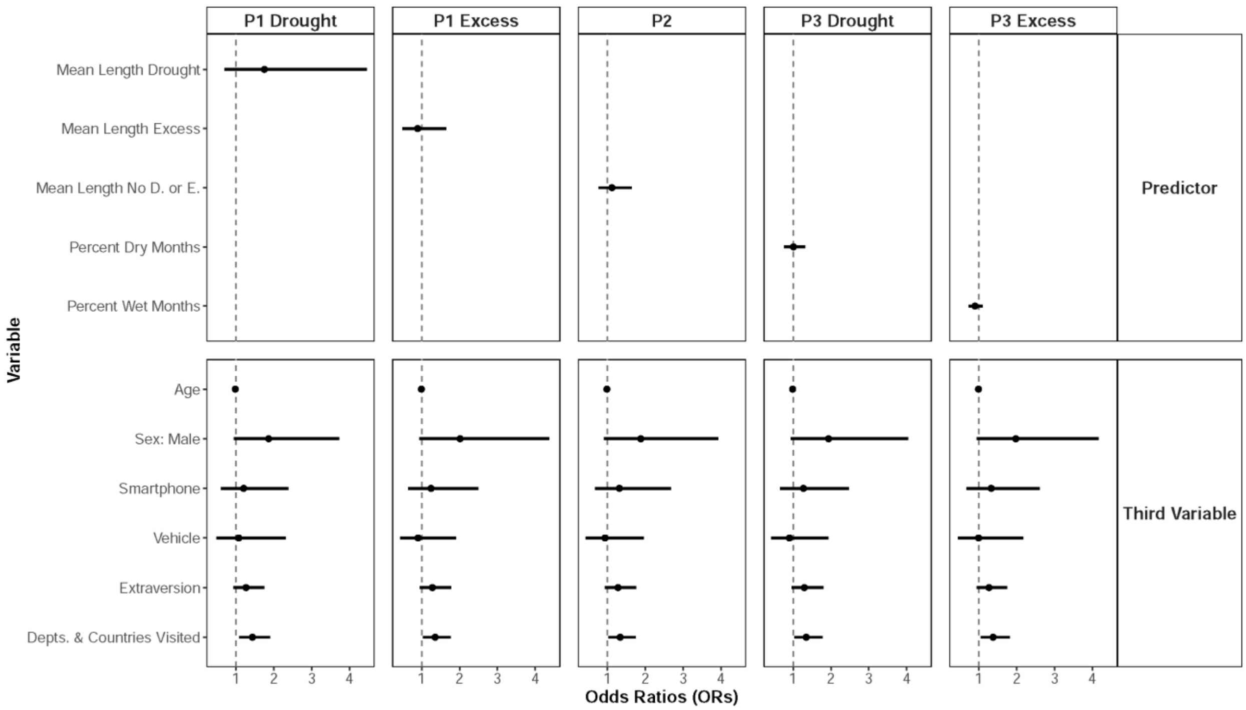


Figure S2. Parameter estimates and 95% credible intervals for an alternative outcome for the five main models: treating *same-community relationships* as the outcome.

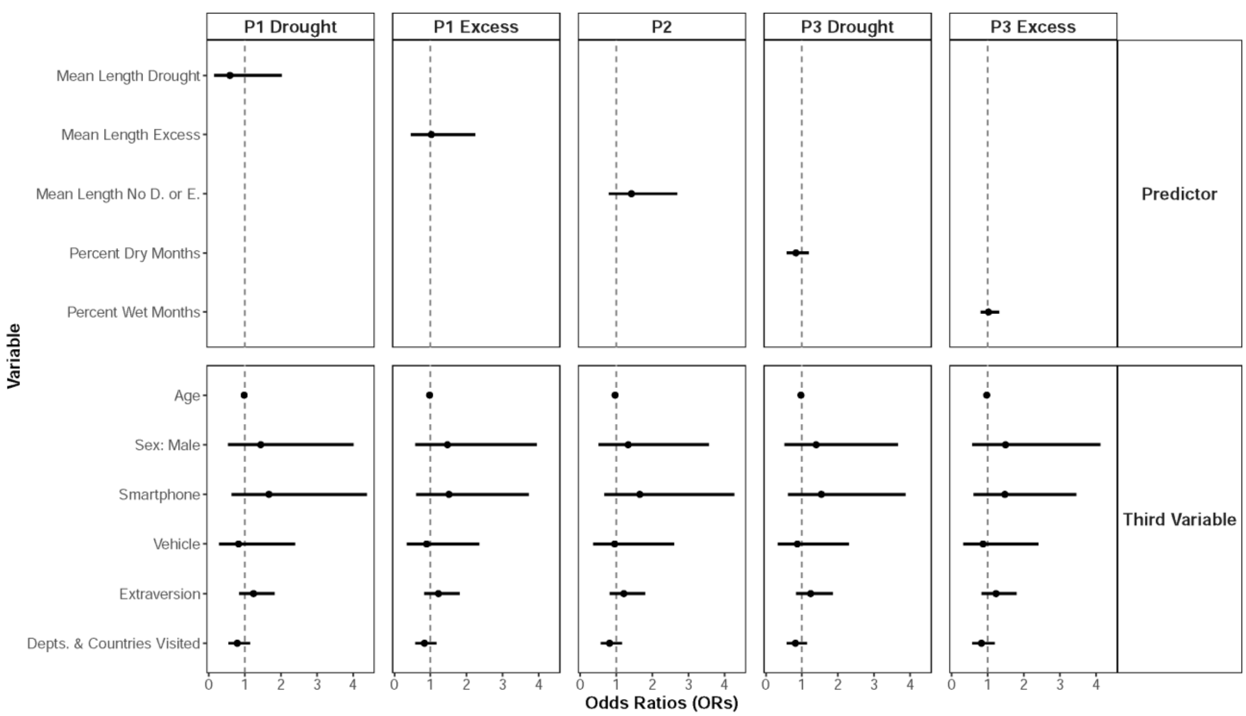
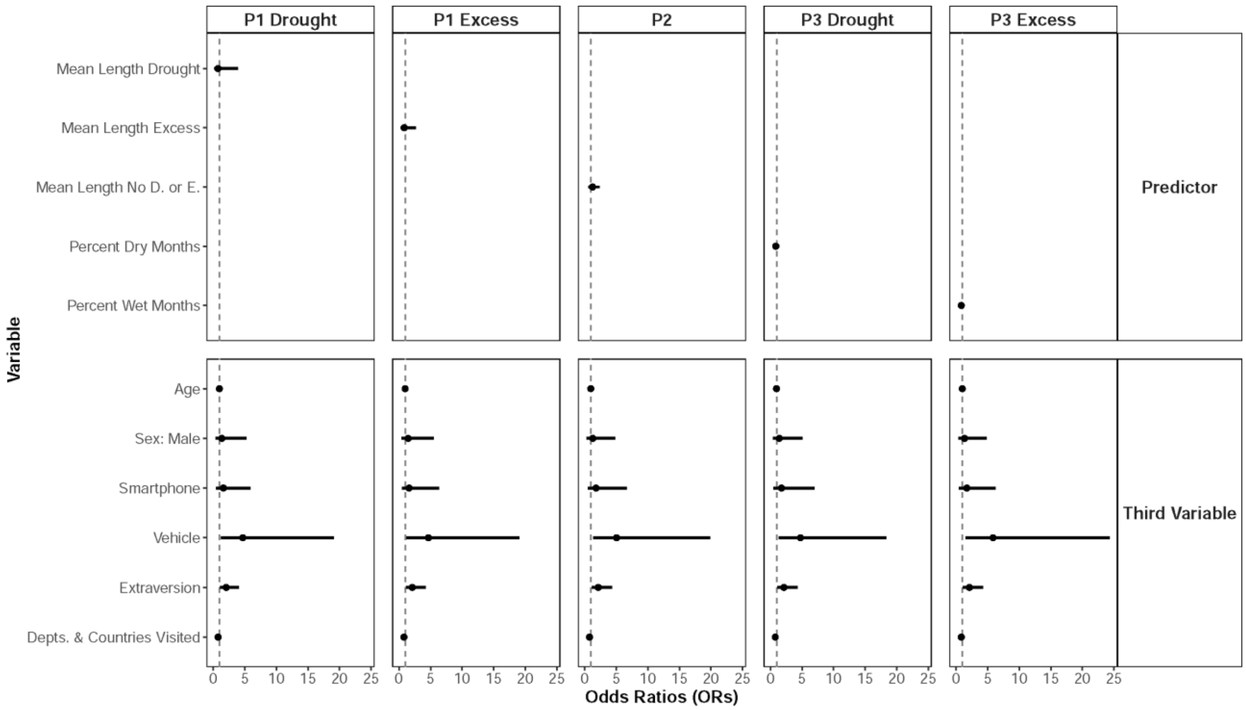


Figure S3. Parameter estimates and 95% credible intervals for a robustness check of the alternative outcome for the five main models: treating *non-consanguineal same-community relationships* as the outcome.



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