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# Complex climate effects on cooperation and disputes in transboundary river basins

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## Abstract

A growing body of evidence suggests a link between climate and conflict. In contrast, the link between climate and cooperation remains much less investigated, although it has been studied in the context of transboundary river basins. Even for transboundary waters, however, earlier results have not decisively answered whether the effect of climate on conflict or on cooperation is stronger. Here we concurrently investigate both cooperation and conflict in transboundary river basins across the world as two potential responses to changes in climatic factors. Our results indicate that one-standard deviation changes in climate variables affect cooperation more than conflict in absolute terms, although effects on conflict are large in relative terms. Furthermore, lower water availability is associated with worse outcomes both through fewer cooperation events and more frequent conflicts. While higher temperatures are associated with more frequent cooperation, the projected decrease in precipitation and soil moisture projected for many regions of the globe may offset positive effects of temperature, and reinforcing cooperative activities should therefore be a policy priority. It is clear that including a full set of potential responses – positive, negative and none - are needed to understand the climatic influence on regional human cooperation and conflict. We encourage further studies that investigate such full-spectrum effects also for other situations than transboundary river basins.

**Keywords:** Climate and conflict, Transboundary rivers, Water resources, International river basins, Econometrics, Cooperation.
**JEL Classification:** Q25; Q54; Q56

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## Introduction

The question of whether climate is associated with the risk of international and regional-scale conflicts and disputes has spurred increasing attention from the research community in recent years. New datasets and approaches have led to a veritable surge of investigations (e.g., Scheffran and Battaglini 2010; Okpara et al. 2016; Serdeczny et al. 2016), which have lately also been fueled by disagreements over methods, results and conclusions (Buhaug 2010; Scheffran et al. 2012; Raleigh et al. 2014; Hsiang and Meng 2014; Cane et al. 2014). Naturally, as emissions of greenhouse gases continue to rise (Myhre et al. 2013), with attendant effects on the climate system in many regions of the globe, the issue is also of great importance to human society and its adaptation to climate change (Carleton et al. 2016; Carleton and Hsiang 2016).

A recent review urged for caution in drawing conclusions about a link between climate and regional conflicts (Bernauer et al. 2012). However, although the authors emphasize that previous studies have not always shown robust results, the review acknowledges that conflicts may arise in certain situations due to climate stress. Reinforcing this notion, a recent synthesis article of quantitative climate-conflict research concluded that a large majority of the 60 papers surveyed therein indicated a link between climate and conflict (Hsiang et al. 2013). The types of conflicts studied in these syntheses are generally violent in nature, but some nonviolent effects are also included, such as removal of political leaders (Hsiang et al. 2013). Over a range of regions and temporal scales, and across different types of climatic influence, these results suggest a clear effect of climate on human conflicts and disputes.

Whether violent or non-violent, disputes also have a counterpart: cooperation. There are reasons to believe that cooperation, as well as disputes, could be affected by climate factors. If disputes can arise over a resource that is stressed by climate, as evidence suggests, the tendency to cooperate over the resource could also be adversely affected. On the other hand, a common resource under stress could conceivably also increase the incentive to cooperate, as a way to avoid greater combined losses.

Cooperation, however, has been less in focus in quantitative studies of climate effects. For example, it was not a possible outcome in any of the studies surveyed in Hsiang et al. (2013). The reason for this might be difficulties in quantifying cooperation – conflicts and disputes can be more transparent and easily recorded. However, that does not mean that cooperation is less relevant. By disregarding one half of the spectrum of outcomes, one runs the risk of artificially truncating the outcome variables, possibly biasing the results. Cooperation has been explored somewhat more extensively, though, in an area where it is clearly more widespread than conflict (Wolf 2007): transboundary water resources. We will focus on such regions for this study of the link between climate, disputes, and cooperation.

Several factors motivate the study of transboundary water resources as an arena for both disputes and cooperation. First, despite strong evidence of cooperation being much more common than conflicts over water in the past (Wolf 2007), the notion of potential disputes over water in a changing climate remains persistent (Barnaby 2009). Second, transboundary river basins involve a physical resource that is both inherently cross-boundary and clearly depends on climate, properties that are highly relevant to an investigation of climate effects on international disputes and cooperation. Third, a river acts as an integrator of the upstream climate, within a clearly defined geographical boundary, and therefore allows a measurable physical state at a point to be meaningfully compared to water-related social events within the basin as a whole.

A number of studies of transboundary water resources have shown evidence of a link both between climate and cooperation, as well as between climate and disputes (Yoffe et al. 2004; Stahl 2005; Hensel et al. 2006; Brochmann and Hensel 2009; Dinar et al. 2010; De Stefano et al. 2012). In contrast to the studies synthesized in Hsiang et al. (2013), water-related conflicts have generally been non-violent in nature, and mostly take the form of disputes and disagreements, although there are also cases of military confrontation.

The studies on transboundary water resources have contributed with a number of important insights, but recent synthesis and review studies have concluded that there is no consensus yet on mechanisms or effect sizes (Johnson et al. 2011; Link et al. 2016), particularly regarding the question of whether climate affects both disputes and cooperation in the same way. To address this question, a number of common limitations in earlier studies have to be overcome.

First, although there are exceptions, the two outcomes of dispute and cooperation have generally been studied in isolation (Furlong et al. 2006; Hensel et al. 2006; Hamner 2009; Stinnett and Tir 2009; Brochmann and Hensel 2009; Dinar et al. 2010). Since climate can conceivably and simultaneously affect both cooperation and disputes, there is a motivation for allowing them both as possible outcomes in the same investigation. Importantly, this was not done in any of the high quality studies identified in the review by Johnson et al. (2011). There is therefore a motivation to conduct a joint study that allows comparison of effects on either outcome.

Second, several studies only include observations for years when disputes or cooperation occurred, disregarding years when no such outcome was recorded (Yoffe et al. 2004; Stahl 2005; Brochmann and Hensel 2009; De Stefano et al. 2012). This implies that variance in climate variables that takes place in years without disputes or cooperation will be disregarded in identification of the effect of climate on disputes and cooperation. Thus, the sample will be selected based on the outcome rather than including all years, even those where there was no evidence of disputes or cooperation. To avoid such problems, the no event years should also be included, which will let the outcome variable more accurately represent reality.

Third, several studies have focused on static climate measures that remain constant over the period of investigation (Hensel et al. 2006; Stinnett and Tir 2009; Dinar et al. 2014). Although such measures may help in characterizing fundamental differences between basins, they clearly are not useful for capturing the substantial temporal variability in climate and water availability (Devlin and Hendrix 2014), which is of greater interest when studying climate effects over time. In addition, they are also methodologically challenging, as it is very difficult to separate the climate effect from all other ways that basins may differ.

Fourth, many studies (including all of the studies synthesized in Hsiang et al. 2013) assume effects on transboundary water dispute and cooperation to be strictly one-directional, i.e., that the probability of dispute or cooperation is either monotonically increasing or decreasing in climate variables (Hensel et al. 2006; Hamner 2009; Bernauer and Böhmelt 2014). Although this is compatible with a traditional neo-Malthusian perspective, where resource scarcity is conceived as a driving force of conflicts, there are indications that at least for precipitation, conflict responses may be non-linear (Burke et al. 2015) and change sign.

Although some studies have partly addressed these issues (Hensel et al. 2006; Hamner 2009; Dinar et al. 2010; Hendrix and Salehyan 2012; Bernauer and Böhmelt 2014), we are aware of no study that overcomes all the limitations outlined above. Therefore, neither the relative importance of the effect of climate on the two outcomes, nor which variables that actually influence either outcome, has not been decisively established, even for transboundary waters. In this paper, we aim to overcome earlier limitations by studying potential outcomes that span the entire gamut of cooperation and conflict over transboundary waters, considering years with no events and with climate varying over time, and also allowing marginal effects to change sign through polynomial specifications.

In this way, we hope to contribute to a more complete understanding of the relation between climate, conflicts, disputes and cooperation. In the end, the relative importance of a climate effect on disputes and cooperation, and the climate variables through which such effects act, may have large consequences under future climate change.

## Materials and Methods

### *Variables and data*

Defining an outcome as binary (e.g., cooperation or no cooperation) makes both estimation and interpretation easier technically, but truncating the outcome variable and disregarding parts of the spectrum can be misleading if climactic factors are associated with both disputes and cooperation. Here, to include events that span the range from conflict to cooperation, thus addressing the first limitation outlined above, we use data from the Transboundary Freshwater Disputes Database (TFDD; http://www.transboundarywaters.orst.edu/database/), which contains data on both sides of the spectrum. This dataset has been compiled through research at the University of Oregon, and lists over 6400 water-related events between nations that share a river basin for the period 1948-2008. We choose to use the TFDD instead of two other datasets, the International Water Conflict and Cooperation dataset (IWCC; Kalbhenn and Bernauer 2012) and the Water Conflict Chronology (WCC; Gleick and Heberger 2014), for several reasons. The IWCC, although substantially more detailed than the TFDD, has a significantly shorter temporal extent (1997-2007), and it is ultimately temporal variation with water basins that will allow us to identify the parameters of our models, a point also emphasized by Johnson et al. (2011). The WCC, although more up-to-date than the TFDD, does not include cooperation. Finally, the TFDD has been the basis for most studies previously investigating the relation between water disputes, cooperation and climate, which facilitates comparison with previous assessments.

In the TFDD, all cooperative and dispute events are ordered, based on the degree of cooperation and dispute, on a scale from -7 to 7 (see Table A1 in the appendix). Thus, dispute and cooperation both have wide spectra, from verbal expressions of discord to armed conflicts, and from minor official exchanges to the signing of international fresh water treaties, respectively. For this study, we do not distinguish between grades of intensity in dispute or cooperation, and therefore collapse the scale; any outcome between 0 and 7 is assigned a value of 1 and any outcome between -1 and -7 is assigned a value of -1 (Table A1). The results are insensitive to whether we assign the 0 events to the positive or negative side of the spectrum. Although the collapsed scale contains effects of very different magnitude (e.g., declaration of war as compared to minor diplomatic remarks), the more extreme events are very rare (Table A1) and thus contain too little variation to estimate the effect across the entire range of outcomes. Also, the original scale is already collapsed since each scale step contains different types of disputes and cooperation (Table A1). Further collapsing the scale implies that we reduce the ordering of events to only negative or positive events. Hence, we cannot make claims about the intensity of the effect, e.g., how much worse a dispute gets in the face of climate stress, but only claims about the probability of some type of cooperation or dispute occurring. We argue that this limitation is acceptable, as our main purpose is to investigate effects on cooperation and dispute as overarching categories of responses.

For a few basins and years, both positive and negative outcomes were occasionally observed in the same year. For those years, we determined an annual value based on the sign of the average outcome in the year. We then extended the dataset of positive (1) and negative (-1) events by assigning a value of 0 to all years where no event occurred, addressing the second limitation in the introduction, in order to obtain a balanced panel and not select observation based on years where an event actually occurred.

To explain the annual dispute-cooperation responses in our modified TFDD dataset, we aggregate a suite of climate data into four explanatory variables over the same period. Principally, we expect river basin dispute or cooperation to be associated with water, and therefore define three variables pertaining to water availability: precipitation, soil moisture (as an indication of drought), and river discharge. We also include temperature, a common variable to use in climate and conflict studies, including half of the studies surveyed in Hsiang et al. (2013). Although we acknowledge that socio-economic factors such as income, trade, and institutions likely also influence outcomes, we do not introduce separate control variables for these factors, as they are often themselves a function of climate (Hsiang et al. 2013), and therefore might bias estimates of the actual climate effect. However, we introduce basin dummies that to some extent capture slow moving basin specific characteristics such as institutional quality.

Of the four variables, precipitation, soil moisture and temperature are clearly exogenous, while an effect of human intervention is possible for discharge. Thus, this variable, although clearly a direct physical measure of time-varying water availability, also risks introducing precisely the type of bad control described in the previous paragraph. Hence, we focus our analysis on the exogenous variables, and only investigate discharge at a later stage to see whether there is any association. We also discuss potential sources of bias and how the causal effect of this important variable could possibly be isolated.

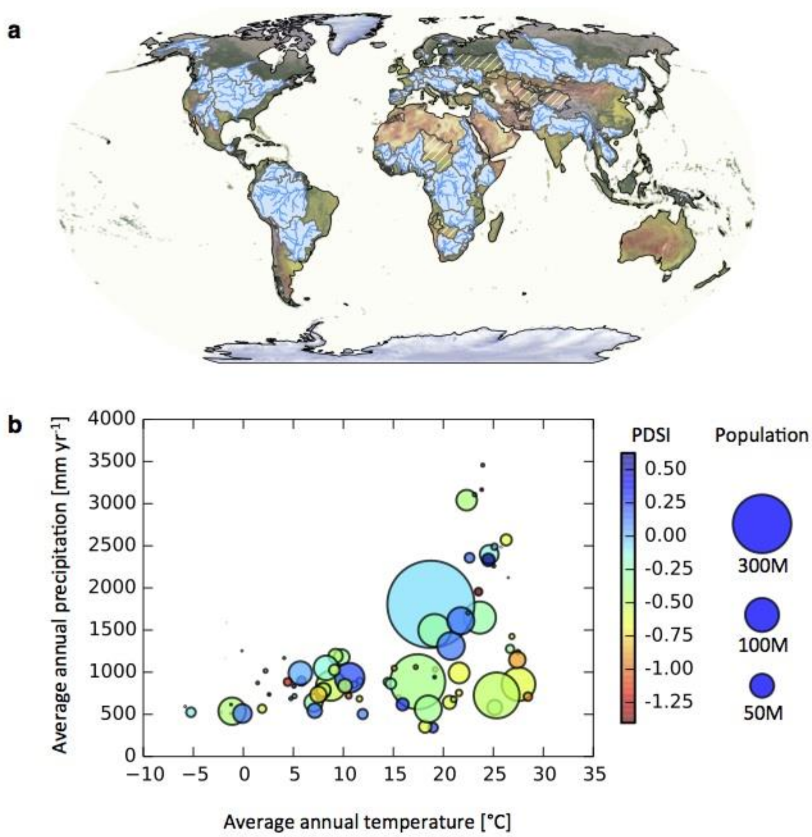


**Fig. 1** Transboundary basins used to investigate climate effects on cooperation and dispute. (a) The 83 basins highlighted in blue are a subset of the Transboundary Freshwater Disputes Database (TFDD) for which we assembled climate and water flow data. Hatched TFDD basins are excluded either on basis of not meeting a minimum size to allow climate data evaluation, or due to lack of reliable long-term discharge data. (b) Geographical characteristics of transboundary basins. Circle positions illustrate the average temperature and precipitation conditions in the 83 basins during our study period 1948-2004. Circle sizes denote basin populations, assembled from the Gridded Population of the World database for the year 2010 (Pozzi et al. 2003), available at http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count-future-estimates). Circle colors represent the long-term average soil moisture, expressed as the Palmer Drought Severity Index (PDSI), for the basin. Negative (positive) PDSI values represent dry (wet) conditions, with values below -3 corresponding to severe drought.

Our final dataset consists of observations between 1948-2008 on 83 basins that combined are home to about 2.5 billion people and span a wide range of climatic conditions (Figure 1; basin details in Table A2 in the appendix). Although this sample is limited in relation to the total number of transboundary basins (267 are defined in the TFDD), our sample contains the vast majority of the human population that resides in such basins (86% of the human population residing in TFDD basins is included in our sample). Therefore, even if the 83 basins differ in some significant way from other basins, which would limit the external validity of our results, we consider the sample satisfactory to the study of international river basins from a societal point of view.

*Model*

Our panel data allow us to identify the effect of climate variables on our outcome variable using variance in variables within basins over time, rather than differences across basins (see Hsiang et al. (2013) and Carleton and Hsiang (2016) for extensive argumentation as to why this is important and how it addresses endogeneity problems). In short, we use basin fixed effects to control for the fact that basins that on average are more prone to, for example, drought, may have a higher probability in general for disputes or cooperation. This addresses the third shortcoming in the introduction, concerning static climate effects, and allows us to use deviations from the basin's average soil moisture to identify an increased or decreased probability of dispute or cooperation from their respectively average probabilities.

As our data is ordinal, we formulate a generalized ordered logit model on the form

$$Y_{it}^{*} = \sum_{c=1}^{3} \beta_{c,o} CV_{c,i,t} + \sum_{c=1}^{3} \beta_{c,o} CV_{c,i,t-1} + B_i + T_t + \varepsilon_{it} = z_{it} + \varepsilon_{it} \quad (1)$$

as our basic setup. $Y^{*}_{it}$ is the latent variable that determines the outcome for each basin and year, which are indexed *i* and *t* respectively. *CV* is a vector of climate variables (1 year lagged values are included in our baseline specification), the different *β*s are coefficient vectors that are indexed *c* for each climate variable and *o* for each outcome. The latter implies that a separate set of parameters are estimated for each outcome, which allows the effect of a climate variable on the probability of a particular outcome to differ for, say, dispute and no event. *B* is a vector of basin fixed effects, *T* a vector of time fixed effects, and *ε* is an error term with a cumulative logistic distribution. We describe the model more in depth in the Appendix.

We base our regression model on the assumption that a year with a large deviation from the average climate may constitute a stress on the basin. An important feature of the generalized ordinal logit model we use is that the proportional odds assumption is relaxed and we can, hence, estimate one set of coefficients for each category relative to our baseline outcome, which in our case will be cooperation. In other words, we allow for different coefficient estimates for each category. In our model, we address the fourth limitation about monotonically increasing or decreasing effects by testing the robustness of our results by adding a quadratic specification of climate variables. Thus, we do not strictly follow the traditional neo-Malthusian perspective of one-directional effects. Rather, our expectation of potential causal mechamisms more closely resembles the "scarperation" idea of Dinar et al. (2007), whereby a U-shaped relationship is hypothesized. Although their model only refers to cooperation, we see no reason such non-linear effects should not be possible also for conflicts.

We estimate the relationship between our climate variables and the outcome variable using the baseline specification described by Equation 1. To test the robustness, we estimate perturbations of our baseline model to account for various ways that timing of climate factors might drive outcomes. The first specification is estimated without the time fixed effects; the second specification includes them. In the third specification we test the model without lagged values of the climate variable, in the fourth specification we add an additional two-year lag of each climate variable. In the fifth specification we use a quadratic specification of each climate variable. In the sixth specification we add the endogenous variable discharge to see if it has any explanatory value for dispute or cooperative outcomes.

**Results and Discussion**

We present the results of our baseline specification in terms of estimated average partial effects in Table 1. The numbers should be interpreted as the marginal effect on the probability of an outcome, in percentage points (pp), due to a one unit increase in the climate variable (1 pp is equal to an absolute probability change of 1%; e.g., a change from 5% to 6%). A unit increase in each variable corresponds to 100 mm/yr for precipitation, 1

°C for temperature, a shift in 1 of the Palmer Drought Severity Index for soil moisture, and 100 $m^3/s$ for discharge. Columns 1, 2, and 3 in Table 1 represent the effects on conflict, status quo, and cooperation outcomes, respectively. In Table A3 in the appendix, we present the coefficients of the model for all specifications. The robustness test did not alter the results in any significant way, so from here on, we discuss results for the baseline specification.

**Table 1** The average partial effect of a unit change[1] in each climate variable on the probability of conflict, status quo, and cooperation. Standard errors are listed in parentheses. Asterisks denote the level of significance for each variable and outcome combination: ***: $p$<0.01, **: $p$<0.05, *: $p$<0.1. Units are percentage points (pp; 1.0 represents 100 pp), where 1 pp equals an absolute change of 1% in the probability of each outcome (e.g., from 0.05 to 0.06, or 5% to 6%).

| VARIABLES | (1) Dispute | (2) No Event | (3) Cooperation |
|---|---|---|---|
| Precipitation | -0.0080** | 0.0078 | 0.0002 |
| | (0.0040) | (0.0056) | (0.0045) |
| Soil moisture | 0.0009 | -0.0071* | 0.0061* |
| | (0.0028) | (0.0040) | (0.0034) |
| Temperature | 0.0013 | -0.0193*** | 0.0180** |
| | (0.0025) | (0.0073) | (0.0070) |
| Observations | 4,603 | 4,603 | 4,603 |

[1]A unit increase in each variable corresponds to 100 mm/yr for precipitation, 1 °C for temperature, and a shift in 1 of the Palmer Drought Severity Index for soil moisture. (see Table A2 with descriptive information).

Our results indicate that for the conventional significance levels, a higher level of precipitation is associated with a lower probability of dispute, while the effect on cooperation is largely insignificant. Higher soil moisture is estimated to increase the probability of cooperation, and the same holds true for higher temperature. Looking at the effects in detail, an increase in precipitation by 100 mm/yr is predicted to, on average, decrease the probability of conflict that year by 0.8 pp. A unit increase in the soil moisture index is predicted to decrease the probability of no event and increase the probability of cooperation by about 0.6-0.7 pp. An increase in temperature by 1 °C is predicted to decrease the probability of no event and increase the probability of cooperation by about 1.8-1.9 pp. For comparison, the average probabilities of dispute, status quo, or cooperation across all basins in any given year are 3%, 80%, and 17%, respectively. Hence, the effects are substantial in relative terms.

To show the relative size of the effects, we plot the predicted average probabilities of dispute, no event, and cooperation for our three exogenous climate variables precipitation, soil moisture, and temperature. We use Equation A4 in the Appendix and keep the variables that do not vary constant at their average values. Naturally, the variability for each climate variable differs substantially between basins. Hence, we calculated average maximum and average minimum of precipitation/soil moisture/temperature across basins, and plot the probabilities over these values.

The generalized ordinal logit model is non-linear, and thus gives non-constant marginal effects. In Figure 2, we see that the relative effect of precipitation on the probability of dispute is quite large (a standard deviation in precipitation is 499 mm/yr). Similarly, the effect of soil moisture on the probability of cooperation is relatively large, which is also the case for the effect of temperature on cooperation, but estimates are much more imprecise for the latter effect. For clarity, these probabilities are estimated controlling for basin-specific conditions. Hence, some basins with, for example, lower precipitation might have higher estimated probabilities of dispute than basins with more precipitation, but on average, the probability of dispute is estimated to decrease with higher precipitation levels.

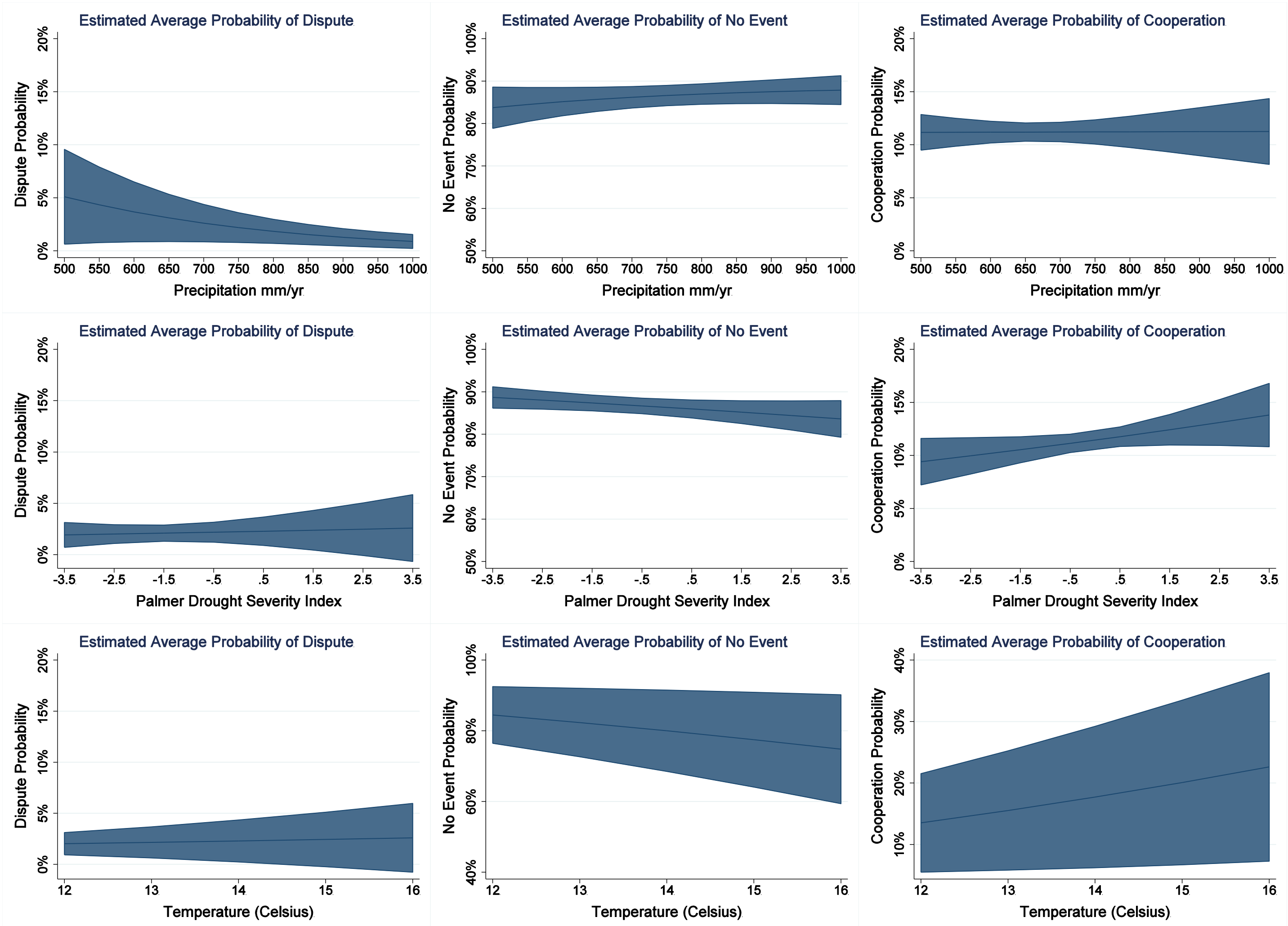


**Fig. 2** Estimated average probabilities of dispute, no event, and cooperation, respectively, plotted over average maximum and minimum values of precipitation, soil moisture, and temperature. For all variables, we keep the other variables fixed at their average levels. Shaded areas correspond to 95% confidence intervals.

Clearly, the graphs show that our model estimates no correlation between precipitation and cooperative outcomes, and no correlation between soil moisture and temperature with disputes. While these results are robust, it is not clear what the exact mechanism is. We note, however, that the overall results are consistent with an often-suggested pathway between resource stress and more negative outcomes (Johnson et al. 2011), despite the complex patterns across outcomes and variables in our study. First, the significant effects for both water variables indicate that outcomes are better when more water is available (fewer disputes and more cooperation as consequences of precipitation and soil moisture increases, respectively). Similarly, although higher temperature could in general put stress on resources (Lobell and Field 2007; Burke et al. 2009; Salehyan and Hendrix 2014), the effect may instead be positive, as seen in our results, when controlling for water availability as we do (i.e., if high temperatures are associated with droughts, such effects are accounted for and not driving our results). For example, as long as temperatures stay below certain thresholds, yields of some of the most common crops increase with temperature, until certain thresholds are reached (Schlenker and Roberts 2009). Therefore, our results may reflect such positive resource effects of increasing temperature, as long as threshold values are rarely reached, or reached only for a small share of years and basins (the latter may in turn also contribute to the imprecise estimates for temperature).

Alternatively, the positive effect of higher temperatures on cooperation may reflect other mechanisms, such as high temperatures acting as a signal of future climate change that in turn spurs cooperation efforts. As noted before, controlling for precipitation and soil moisture, temperature itself would then not affect water supply directly, while lower precipitation and soil moisture would immediately affect productivity and hence decrease the probability of cooperation and increase the probability of dispute, respectively. Our data, however, is not detailed enough to explore the validity of any of the above-mentioned explanations. To investigate these potential mechanisms in detail, a much more detailed study would have to be undertaken, carefully designing variables to isolate the effect of climate variations through such intermediate pathways. Ideally, case studies could here be used to identify potential factors, whose influence can then be quantitatively estimated using large-N studies. We now turn to explore the relative size of the estimated effects and the heterogeneity of marginal effects across basins.

Over time, the individual basin variations in precipitation, soil moisture, and temperature span a decisively smaller range than the values over which the probabilities are plotted in Figure 2. Hence, to facilitate the interpretation of the effect size, we can look at relative changes in probability, although it should be kept in mind that many basins have an estimated baseline probability of dispute that is virtually zero. For those basins, even an infinitesimal increase in the probability of dispute would lead to a very large relative increase. Therefore, we also investigate the effects – in relative terms only – of a more plausible, basin-specific standardized change in the following way: We use equation A4 in the SI to calculate the basin-specific estimated probability of dispute, cooperation, and status quo, conditional on individual basin-averages for each climate variable (year is set to 2004). We explore a change in conditions in line with predicted effects of global warming for many (but not all basins), a decrease in precipitation and soil moisture and an increase in temperature. We calculate basin-specific standard deviations of precipitation, soil moisture, and temperature, and subtract and add these, respectively, from the basin-average values of the variables.

Using this calculated value, we predict a new estimated probability of each outcome while holding other values constant. In Table 2, we present the average relative change in probability of each outcome, due to the basin-specific one standard deviation change in each one of the climate variables.

**Table 2** Estimated relative change (in %) and absolute (in percentage points, pp) in outcome probabilities, due to a basin-specific decrease of one standard deviation in precipitation and soil moisture, and a standard deviation increase in temperature respectively averaged across all basins.

| VARIABLE | | (1)<br>Dispute | (2)<br>No Event | (3)<br>Cooperation |
|---|---|---|---|---|
| Precipitation | | | | |
| 1 sd decrease | *Relative* | 53.3% | -0.4% | -0.2% |
| | *Absolute* | 0.39pp | -0.37pp | -0.02pp |
| Soil moisture | | | | |
| 1 sd decrease | *Relative* | -6.3% | 1.9% | -9.9% |
| | *Absolute* | -0.06pp | 1.23pp | -1.17pp |
| Temperature | | | | |
| 1 sd increase | *Relative* | 4.1% | -2.4% | 13.6% |
| | *Absolute* | 0.04pp | -1.56pp | 1.52pp |
| Average Probability | | 1% | 82.2% | 16.8% |

First, we note that the only associations that were significant at conventional significance levels were precipitation with dispute, and soil moisture and temperature with no event and cooperation. The non-significant relative effects can still be large, such as the effects of soil moisture and temperature on disputes, which are on the order of 4-6%. However, for these cases, the absolute effects (derived using our non-statistically significant coefficients from Table 1) are very small: shifts in probabilities equal to 4-6/100 of a percentage point hardly matter in practical terms, and the large relative effect sizes are in these cases due to the low baseline dispute probability.

Table 2 presents the average effect across all basins. The marginal effects of a change in a climate variable differ across basins due to the non-linearity of the generalized ordinal logit model and due to each basin specific average climate values, as well as basin specific characteristics, that are captured by the basin fixed effects. Hence, rather than just looking at the average, it is also of some interest to look at the distribution of the effects across all individual basins. For the effects that are estimated to be statistically significant and substantial in absolute terms (precipitation on dispute; soil moisture and temperature on cooperation), Figure 3 shows the estimated kernel density of the estimated relative marginal effects of the standard deviation changes defined above, using individual estimates for all basins.

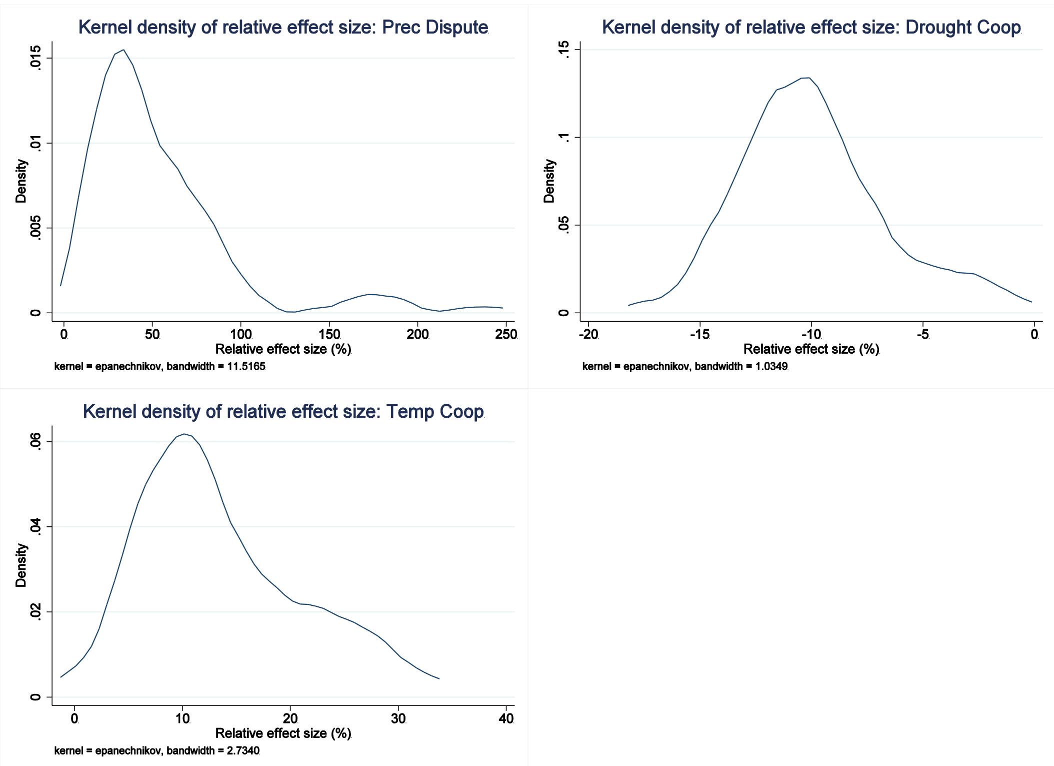

**Figure 3.** Kernel density of relative effect sizes of a) precipitation on disputes, b) soil moisture on cooperation, and c) temperature on cooperation.

The distribution of the precipitation effect is right skewed, which again is due to the fact that a few basins have estimated probabilities of dispute that are almost zero, so minor absolute effects give rise to very large relative effects. However, the bulk of the effect of a one-standard deviation decrease in precipitation is an increase in dispute probability of between 0 and 100%. Although the marginal effect has a peak around 50%, there is substantial heterogeneity across basins. The marginal effects of soil moisture and temperature show the same type of heterogeneity. A basin-specific one standard deviation decrease in soil moisture is estimated to have a negative effect on the probability of cooperation of between 0 and 18%. Similarly, a basin-specific one standard deviation increase from the basin mean in temperature is predicted to increase the probability of cooperation by between 0 and 30%.

Since these results were derived using basin specific standard deviations, we see that there is not only an overall statistical association between our climate variables and dispute and cooperation, but that effects are mostly of substantial size also across basins. There is, however, large heterogeneity in the marginal effects of each variable across our 83 basins. An increase in precipitation is on average related to a decrease in dispute probability, while cooperation probability increases both with wetter soils and warmer conditions.

While the mechanisms are not entirely straightforward, our results are robust. In the appendix, we show the estimated coefficients across all our different specifications. If we omit time fixed effects, or vary the number of lags between 0 and 2, we only see minor quantitative changes in coefficients, but no qualitative differences to our results. For precipitation, the quadratic term is significant, and when included also yields a significant association between precipitation and cooperation. However, when the quadratic specification is used to calculate average marginal effects, the point estimates stay close to our baseline specification. In our final specification, we added discharge as an explanatory variable, but found no statistically significant relationships between discharge and outcomes. The discharge variable is endogenous in the model, as discharge might also be an outcome of either conflict or cooperation, in addition to causing it firsthand. We will not dismiss the potential explanatory power of discharge, and in future research hope to develop methods to overcome the endogeneity problems by separating the anthropogenic – and therefore potentially endogeneous and dispute- or cooperation-caused – component of discharge from the background "pristine" discharge. In this way, we could build a model aimed at explaining cooperative and dispute outcomes by better understanding the factors determining discharge and how these vary across basins.

Overall, although only significant for precipitation, our results support the conclusions in Hsiang et al. (2013) of a climate-dispute related link. The overall risk of disputes are low, but for a one-standard deviation decrease in precipitation, the risk of dispute is estimated to increase with between 0 and 100% across basins, with an average of about 50%, or 0.39 percentage points. This is a substantial effect in relative terms, and significantly larger than the average effect size of 14% that was evident across the studies surveyed in Hsiang et al. (2013). In contrast to precipitation, soil moisture and temperature are primarily related to cooperation, with an increase in both variables estimated to increase the probability of cooperation. Interestingly, these climate effects on cooperation are, in relative terms, of approximately the same magnitude (~10-14%) as the effects on conflict documented by Hsiang et al. (2013). However, in absolute terms, the cooperation probability changes due to a one-standard deviation change in soil moisture or temperature are more than twice as large as corresponding changes in conflict probability due to a one-standard deviation precipitation change (1.17-1.56 pp compared to 0.39 pp).

Our results, which comprehensively consider both temporal and geographical variation, have thus demonstrated a complex pattern of effects. For the first time, we study concurrent and global responses of long-term variation in multiple climate variables on both disputes and cooperation. This design revealed that different components of the climate system are linked to positive and negative outcomes. Furthermore, despite our hypothesis that large deviations from basin averages should possibly incite disputes or spur cooperation, we find only very weak evidence for such responses. Instead, the effect is monotonically increasing or decreasing with change in the climate state, but our non-linear model nonetheless allows responses to vary in a more nuanced way than most earlier studies, also for the multiple-outcome design that we introduce here.

Water and other environmental issues are potential entry points to wider cooperation, and may thus help mitigate conflict tendencies between nations (Najam 2013). Therefore, even when considering a large body of research indicating a tendency to cooperate over shared waters (Wolf 2007; Tir and Stinnett 2012), our results give some reason for concern when considering future expected changes to the climate. Although our estimates indicate that temperature increases have positive effects on cooperation when controlling for water availability, global projections indicate substantial decreases in the latter (Collins et al. 2013). Over much of the mid-latitudes, including the Mediterranean, Middle East, and much of Central and South America and Southern Africa, precipitation is projected to decrease (Collins et al. 2013). For soil moisture, a substantial decrease is projected over the same regions, and in a high-emission scenarios also for much of Europe and North America (Collins et al. 2013). Therefore, irrespective of the mechanism, the positive effects of warming on cooperation may be offset by a concurrent drying, should dispute and cooperation responses to such variations behave similarly in the future as in the past. Likelihood estimates for such projections vary, however, and the uncertainty over a number of regions is very large. To provide more reliable estimates of future water availability, which is of critical importance to attempt any projection of climate-driven effects on conflict and cooperation, improvement in climate model land surface schemes should be a research priority (Bring et al. 2015; Jaramillo and Destouni 2015).

We have studied effects on the scale of entire river basins, while in some cases, several countries with territory in the basin may not have been involved in the events we investigate. Therefore, our results pertain principally to effects of basin-wide climate signals. Future studies may yield more detail on how effects vary between country-pairs within basins, perhaps also using more precise delineations of transboundary basins (Beck et al. 2014). However, such investigations would also require more finely resolved climate data than is generally available for many basins.

## Conclusions

While cooperation over transboundary water resources is more common than disputes, our results indicate that climate has an effect on both outcomes, and that effects on cooperation are markedly stronger in terms of the absolute number of events, when considering a one-standard deviation in different climate variables. This result is not simply a consequence of our novel way of specifying the problem, where we use a single model to estimate several outcomes simultaneously, but is clearly significant in terms of magnitudes of the effect, and also in a statistical sense. The influence of climate on dispute probability is decreasing in absolute terms as precipitation increases. In contrast, the effect of climate on the probability of cooperation increases with wetter soil moisture conditions and increase in temperatures. Although our results strictly apply to past events, they still give some reason for concern about future conditions for transboundary water conflict and cooperation as precipitation and soil moisture are projected to decrease across much of the mid-latitudes. Conflicts over water are mostly non-violent in nature, in contrast to other climate-driven conflicts investigated previously (Hsiang et al. 2013), but a decrease in cooperation due to lower water availability may still worsen outcomes overall.

We emphasize that no quantitative study, including ours, can aspire to exhaustively represent the interplay between climate, conflict and cooperation. A wide range of factors, pertaining to institutional, political and historical context, among other things, are also critical for understanding mechanisms of human cooperation and conflict, whether the issue at stake is transboundary water resources (Gleick 1998; Wolf 2007; Van der Zaag 2009; Islam and Susskind 2012) or water resources in general (Pederson et al. 2012; Grantham and Viers 2014; Böhmelt et al. 2014; Selby and Hoffmann 2014). To further advance our understanding of climatic influences on disputes and cooperation, a mix of case studies and quantitative studies is required (Mobjörk et al. 2010). Nevertheless, our quantitative study has revealed significant relationships between several variables that do play a role, and also provided an estimate of the average effect size as well as an indicator of the heterogeneity in effect sizes across basins, and these aspects remain important to consider in understanding the long-term impact of climate change on disputes and cooperation.

Our findings underline the importance of considering a full spectrum of effects, and we conclude with a recommendation that cooperation should now be brought into a stronger focus of the quantitative climate and conflict research community. A first necessary step in that direction would be the assembly of relevant data sets that allow for concurrent estimations of cooperative outcomes together with conflict. In that way, further studies could shed light on whether a stronger link to cooperation prevails also across other aspects where climate has been linked to more violent conflicts. This might in turn put earlier conclusions about climate change and conflict in a more complete context of inter-state relations, acknowledging that such relations can be both confrontational and cooperative.

**Acknowledgments**

All data used in this paper are freely available online, as specified in detail in the appendix. The research was made possible by use of the Transboundary Freshwater Dispute Database (TFDD), Department of Geosciences, Oregon State University. Additional information about the TFDD can be found at http://www.transboundarywaters.orst.edu. Arvid Bring acknowledges support from the Swedish Research Council VR (project number 2013-7448).

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# APPENDIX

## Supplementary Methods

*Outcome variable: Cooperation and conflict data*

To investigate the potential effect of climate on the cooperation-conflict continuum, we used the Transboundary Freshwater Disputes Database (TFDD), an extensive dataset that includes both cooperation and conflict events, to form our outcome variable. The TFDD is in continuing development at the Department of Geosciences, Oregon State University. The database includes water events "defined as instances of conflict and cooperation that occur within an international river basin, that involve the nations riparian to that basin, and that concern freshwater as a scarce or consumable resource (e.g., water quality, water quantity) or as a quantity to be managed (e.g., flooding or flood control, managing water levels for navigational purposes)" (Yoffe, 2001). All data in the TFDD are available freely online at http://www.transboundarywaters.orst.edu.

*Predictor variables: Climate data*

The climate data that we used as forcing variables consist both of global gridded datasets of precipitation, temperature and soil moisture (a measure of drought), which we extracted for all basins, and of discharge data, which were available at or near the outlets of river basins.

For precipitation and temperature, we downloaded the Willmott and Matsuura v3.1 dataset (available online at http://climate.geog.udel.edu/~climate/), and for soil moisture data, we used a Palmer Drought Severy Index (PSDI) dataset (Dai, 2011; Dai et al., 2004) available at http://www.cgd.ucar.edu/cas/catalog/climind/pdsi.html. These datasets provide monthly values for all land surface areas at 30 minutes' spatial resolution, for the time periods 1900-2010 (Willmott Matsuura) and 1850-2012 (PDSI).

The Willmott Matsuura dataset draws on a number of data sources of original precipitation and temperature measurements, with the total number of stations used for each point in time varying between 4,100 and 22,000 for precipitation and 1,600 and 12,200 for temperature. Station values are estimated for a rectangular grid by means of a climatologically aided interpolation (Willmott and Robeson, 1995). The

Willmott Matsuura precipitation data, together with similar observation-based datasets such as the Climate Research Unit (CRU) products from the University of East Anglia, have been identified as superior to precipitation estimates originating from satellite-based or model-aided reanalysis data in several studies for various parts of the globe (Fekete et al., 2004; Pavelsky and Smith, 2006).

The PDSI data estimates deviations in soil moisture through a physically based water balance model that has been used and shown to be accurate in a wide set of applications for various parts of the world (Dai, 2011). In the version we use, recent improvements to the PDSI have been included, such as a more sophisticated evapotranspiration scheme and a self-calibration approach that overcomes some limitations in the original United States-based development of the model. The PDSI is represented as a dimensionless quantity, with values varying between about -10 and 10. Negative values indicate dry conditions and positive values wet conditions, with values below -3 corresponding to severe drought.

To prepare for extraction of the gridded data for the TFDD basins, we converted the vector-format TFDD basins to grid format at the same 30" resolution as the input climate datasets, using the Data Management toolkit in ESRI ArcGIS v10.1. Subsequently, we removed all basins that consisted of 10 cells or less, in order to sample only basins where a reasonable number of climate data points were available for all years. This corresponded to minimum watershed areas ranging from ~10,000 $km^2$ at 70° latitude to ~31,000 $km^2$ at the equator.

Area-weighted average monthly values were then extracted for all basins and years in the TFDD dataset. This step was performed using UV-CDAT, an open-source climate data analysis platform developed by a consortium led by the Lawrence Livermore National Laboratory and available freely at http://uv-cdat.org. Data were then imported into Stata, and monthly averages were combined into annual average values.

We also compiled a direct measure of water availability in our study basins from a global discharge dataset (Dai et al., 2009); henceforth referred to as the Q dataset, available online at http://www.cgd.ucar.edu/cas/catalog/surface/dai-runoff/). The Q dataset combines discharge observations reported from various national hydrometeorological agencies with a global macro-scale hydrological model to provide harmonized and complete time series of monthly discharge values at the outlet of 925 basins around the world for the time period 1948-2004. We manually inspected all stations in the Q dataset and identified 118 basins that coincided with basins also in the TFDD.

For the Ganges-Brahmaputra and La Plata basins, the Q dataset listed two separate stations, whereas the TFDD treated them as single rivers. For these two basins, we used the sum of their two tributary rivers (Ganges and Brahmaputra rivers and Paraguay and Uruguay rivers, respectively) as the Q value.

In general, the drainage areas of the stations in the Q dataset matched well with the areas of the basin polygons in the TFDD dataset ($R^2 = 0.97$). For a small set of rivers, however, there was an appreciable size mismatch between the listed TFDD basin area and the basin area upstream of the discharge station available in the Q dataset. For the Benito/Ntem (TFDD code: BENT) river, we used Q station no 271, which is centrally located in the basin and drains an area of 18,200 $km^2$, compared to the TFDD listed area of 45,000 $km^2$. For the Jordan (JORD) river, we used Q station no 822, which drains the Yarmuk river of 5,920 $km^2$, compared to the TFDD basin's listed 34,000 $km^2$. For the Tigris (TIGR) river, we used Q station number 57, which is located downstream in the Tigris basin, but is listed as draining only 134,000 $km^2$, compared to the 789,000 $km^2$ of the TFDD data. For the Tuloma (TULM) river we used station 526 in the Q dataset, which drains 3,780 $km^2$ instead of the 26,000 listed in TFDD. For the Yalu (YALU) river, the Q station with number 338 drained 18,245 $km^2$, compared to the 51,000 $km^2$ listed in the TFDD. These differences could indicate divergence between the areas that the Q and TFDD data pertain to, but they could also reflect errors or inaccuracies in the listed contributing areas. We tested our regressions without these basins, and although coefficients changed slightly, neither the main results nor the conclusions were affected.

Our forcing dataset was finalized by selecting all basins for which there were data available in both the Q dataset and the gridded datasets. The final number of basins in this set was 83, out of which 38 basins were at least 50 cells in size and 33 at least 100 cells in size at 30” (0.5 degree) resolution. The sizes and number of cells at 30” resolution for all basins that we include are given in Table A2 in the appendix.

*The model*

In our model, we allow for three different outcomes in every basin $i$ in each year $t$ (positive, status quo or negative). We represent the different outcomes using the variable $Y_{it}$ which takes on the value -1 if there is a negative outcome, 0 if nothing happens, and 1 if there is a positive outcome in basin $i$ in year $t$ on the TFDD BAR scale variable. We consider values of 0 in the original TFDD BAR dataset to be positive outcomes and assign them a value of 1, but our results are insensitive to whether we assign these outcomes to the positive or negative side of the spectrum. To quantify the relationship between our outcome variable and climate variables, we specify an ordered logit model (Woolridge, 2002). What we observe is the discrete outcome variable $Y_{it}$. The actual outcome depends on the unobserved continuous latent variable $Y^*_{it}$. The relationship between $Y_{it}$ and $Y^*_{it}$ is defined by the following rules.

$$Y_{it} = \begin{cases} 1 \quad if \quad Y_{it}^* > \tau_{con} \\ 0 \quad if \quad \tau_{con} > Y_{it}^* > \tau_{coop} \\ -1 \quad if \quad \tau_{con} > Y_{it}^* \end{cases} \qquad \text{(A1)}$$

Where $\tau_{con}$ and $\tau_{coop}$ are cutoffs for conflict and cooperation respectively. We define $Y^*_{it}$ to be a random variable:

$$Y_{it}^* = f(CV_{it}) + B_i + g(t) + \varepsilon_{it} \qquad \text{(A2)}$$

Here, $i$ and $t$ indexes basin and year respectively, $CV$ is a vector of climate variables, $B$ a vector of basin fixed effects, $g(t)$ is a function of time possibly including both time fixed effects and a flexible time trend function, and $\varepsilon$ is an error term with a cumulative logistic distribution. This gives us the ordered logit model, which we can use to estimate the relationship between changes in the climate variables and all three different outcomes. We use an ordered logit model rather than treating the outcomes as points on a cardinal scale because we want to acknowledge that we do not know the distance between -1 and 0 and 0 and 1. Using the ordered logit, we assume that these are points on an ordinal scale where only the ordering of the outcomes matter and not the numeric distance between them.

Our specification of the latent variable used in our ordered logit model is

$$Y_{it}^{*} = \sum_{c=1}^{3} \beta_{c,o} CV_{c,i,t} + \sum_{c=1}^{3} \beta_{c,o} CV_{c,i,t-1} + B_i + T_t + \varepsilon_{it} = z_{it} + \varepsilon_{it} \quad \text{(A3)}$$

where the betas are coefficients and $T$ are time fixed effects. We then define the predicted value of $Y^{*}_{it}$ to be $z_{it}$. Once estimated, the regression coefficients can then be used together with the estimated cutoff points to get conditional predicted probabilities for the three different outcomes.

$$P(Y_{it} = j) = \begin{cases} \dfrac{1}{1+\exp(z_{it} - \tau_{con})}, & if \quad j = -1 \\ \dfrac{1}{1+\exp(z_{it} - \tau_{coop})} - \dfrac{1}{1+\exp(z_{it} - \tau_{con})}, & if \quad j = 0 \\ 1 - \dfrac{1}{1+\exp(z_{it} - \tau_{coop})}, & if \quad j = 1 \end{cases} \quad \text{(A4)}$$

We allow for within-basin correlation of the error terms by clustering the standard errors on a basin level. We estimate a general ordered logit model and relax the parallel odds assumption for the fixed effects by using the gologit2 routine in Stata (Williams, 2006). The ordered logit is a non-linear model so the marginal effects on the predicted probabilities depend on the values of all the independent variables, in particular the fixed effects. For example, basins that have had very few instances of cooperation or conflict might have marginal effects of changes in climate variables that are close to zero.

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**Table A1. Outcome variable.**

| Event description | BAR scale | BAR events | New Classification | New Events |
|---|---|---|---|---|
| Formal declaration of war | -7 | 4 | | |
| Extensive war acts | -6 | 31 | | |
| Small scale military acts | -5 | 43 | | |
| Political-military hostile actions | -4 | 18 | -1 | 138 |
| Diplomatic-economic hostile actions | -3 | 121 | | |
| Strong verbal expression of hostility | -2 | 363 | | |
| Mild verbal expression of discord | -1 | 721 | | |
| Status quo | N/A | N/A | 0 | 8,373 |
| Neutral or non-significant acts | 0 | 273 | | |
| Minor official exchanges | 1 | 1889 | | |
| Official verbal support of goals | 2 | 907 | | |
| Cultural or scientific agreement or support | 3 | 738 | 1 | 685 |
| Economic technological or industrial agreement | 4 | 1149 | | |
| Military economic or strategic support | 5 | 41 | | |
| International freshwater treaty | 6 | 507 | | |
| Voluntary unification into one nation | 7 | 0 | | |

The original BAR scale used in the TFDD dataset, along with our amended classification for this study. Note that the amended data includes a smaller set of basins than the TFDD dataset

**Table A2. List of included basins.**

| TFDD basin code | Full name | Average annual temperature (°C) | Average annual precipitation (mm $yr^{-1}$) | Average annual PDSI value | Average annual discharge ($m^3$ $s^{-1}$) | Drainage area ($km^2$ × 1,000)* | Number of cells at 30' resolution | Population (millions) |
|---|---|---|---|---|---|---|---|---|
| AMUR | Amur | -1.13 | 537 | -0.41 | 9799 | 2093 | 1043 | 65.4 |
| AMZN | Amazon | 24.59 | 2398 | -0.12 | 172655 | 5857 | 1924 | 30.9 |
| ASIX | Asi (Orontes) | 14.43 | 886 | -0.47 | 29 | 38 | 14 | 5.5 |
| BAKR | Baker | 9.06 | 1254 | -0.85 | 861 | 31 | 16 | <0.1 |
| BENT | Benito/Ntem | 23.84 | 3166 | -1.18 | 271 | 45 | 14 | 0.7 |
| CLDO | Colorado | 11.94 | 504 | 0.10 | 395 | 655 | 268 | 9.0 |
| CLMB | Columbia | 5.81 | 895 | 0.35 | 5291 | 670 | 310 | 7.5 |
| CNGO | Congo/Zaire | 23.65 | 1648 | -0.29 | 40402 | 3675 | 1200 | 90.2 |
| CROS | Cross | 26.29 | 2570 | -0.62 | 556 | 52 | 17 | 10.9 |
| CRTY | Courantyne (Corantijn) | 26.49 | 2122 | -0.32 | 1078 | 42 | 15 | 0.1 |
| DANU | Danube | 8.78 | 840 | -0.53 | 6472 | 792 | 371 | 79.1 |
| DNPR | Dnieper | 7.01 | 639 | -0.26 | 1449 | 518 | 273 | 29.1 |
| DNSR | Dniester | 7.78 | 698 | -0.22 | 316 | 62 | 29 | 6.0 |
| DONX | Don | 7.14 | 544 | 0.14 | 693 | 427 | 211 | 18.5 |
| DUGV | Daugava | 5.11 | 717 | -0.07 | 467 | 59 | 32 | 1.6 |
| DURO | Douro (Duero) | 11.65 | 894 | -0.26 | 590 | 99 | 43 | 3.9 |
| EBRO | Ebro | 11.61 | 684 | -0.57 | 416 | 86 | 36 | 2.8 |
| ELBE | Elbe | 7.90 | 777 | -0.26 | 690 | 133 | 69 | 21.5 |
| ESQB | Essequibo | 25.05 | 2261 | 0.03 | 2166 | 238 | 78 | 0.8 |
| FRSR | Fraser | 2.22 | 1016 | -0.15 | 2779 | 241 | 129 | 1.2 |
| GAMB | Gambia | 27.46 | 1239 | -0.97 | 171 | 70 | 21 | 1.6 |
| GANG | Ganges-Brahma-putra-Meghna | 18.75 | 1806 | -0.08 | 32356 | 1629 | 598 | 666.5 |
| GJLV | Grijalva | 22.62 | 2357 | 0.15 | 531 | 126 | 43 | 8.3 |
| GLAM | Glama | 1.43 | 873 | -0.13 | 678 | 43 | 26 | 0.7 |
| GRON | Garonne | 11.10 | 856 | -0.69 | 563 | 56 | 25 | 3.8 |
| GUDN | Guadiana | 15.52 | 704 | -0.12 | 156 | 68 | 27 | 1.5 |
| HANX | Han | 9.84 | 1179 | -0.34 | 482 | 35 | 15 | 21.5 |
| HSIX | Hsi (Bei Jiang) | 19.13 | 1496 | -0.28 | 1339 | 417 | 149 | 93.2 |
| ICMT | Incomati | 19.18 | 1033 | -0.88 | 66 | 47 | 15 | 2.0 |
| INDU | Indus | 17.44 | 887 | -0.37 | 2548 | 1138 | 425 | 264.8 |
| IRWD | Irrawaddy | 22.33 | 3041 | -0.40 | 8675 | 401 | 137 | 37.2 |
| JORD | Jordan | 18.97 | 342 | 0.21 | 8 | 34 | 12 | 8.1 |
| JUBA | Juba-Shibeli | 25.13 | 582 | -0.24 | 192 | 800 | 261 | 19.5 |
| KEMI | Kemi | -0.14 | 1253 | 0.62 | 567 | 56 | 48 | 0.1 |
| KMOE | Komoe | 26.86 | 1425 | -0.71 | 180 | 78 | 24 | 2.3 |
| KRLV | Klaralven | 5.06 | 837 | 0.24 | 527 | 51 | 33 | 1.2 |
| LMPO | Limpopo | 20.61 | 642 | -0.62 | 127 | 414 | 149 | 15.4 |
| LPTA | La Plata | 20.76 | 1312 | 0.12 | 22111 | 2947 | 1051 | 66.7 |
| MEKO | Mekong | 21.75 | 1610 | 0.14 | 9930 | 785 | 264 | 63.8 |
| MISS | Mississippi | 10.62 | 934 | 0.21 | 17473 | 3230 | 1376 | 77.1 |
| MPUT | Maputo | 17.24 | 1061 | -0.80 | 72 | 31 | 12 | 1.3 |
| MRNI | Maroni | 25.78 | 2483 | -0.47 | 1660 | 65 | 21 | <0.1 |
| MRSA | Maritsa | 10.53 | 721 | -1.00 | 109 | 50 | 20 | 3.1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| NELS | Nelson-Saskatchewan | 1.87 | 567 | -0.57 | 2206 | 1113 | 582 | 6.1 |
| NGER | Niger | 27.52 | 858 | -0.61 | 5760 | 2105 | 715 | 99.4 |
| NILE | Nile | 25.33 | 725 | -0.48 | 558 | 3020 | 1011 | 184.1 |
| NRVA | Narva | 4.75 | 687 | 0.04 | 379 | 53 | 35 | 0.9 |
| OBXX | Ob | -0.09 | 510 | 0.12 | 12777 | 2964 | 1751 | 30.7 |
| ODER | Oder (Odra) | 8.05 | 791 | -0.53 | 523 | 123 | 62 | 16.5 |
| OGOO | Ogooue | 23.94 | 3457 | -0.30 | 4693 | 222 | 73 | 0.8 |
| ORAN | Orange | 18.18 | 355 | -0.62 | 193 | 944 | 340 | 13.2 |
| ORIN | Orinoco | 24.50 | 2333 | 0.62 | 31813 | 923 | 308 | 14.1 |
| OUEM | Oueme | 26.68 | 1277 | -0.30 | 178 | 59 | 19 | 6.0 |
| PANG | Pangani | 21.05 | 679 | -0.41 | 27 | 49 | 16 | 2.9 |
| POXX | Po | 9.22 | 1193 | -0.42 | 1513 | 87 | 40 | 17.7 |
| PSVK | Pasvik | -1.30 | 509 | 0.33 | 157 | 16 | 14 | <0.1 |
| PUNG | Pungoe | 22.48 | 1704 | -0.22 | 117 | 30 | 10 | 1.0 |
| RGNA | Rio Grande (North America) | 15.93 | 619 | 0.26 | 28 | 655 | 247 | 13.2 |
| RHIN | Rhine | 8.27 | 1051 | -0.15 | 2243 | 173 | 89 | 53.1 |
| RHON | Rhone | 9.11 | 1026 | -0.50 | 1701 | 100 | 46 | 10.3 |
| SABI | Sabi | 21.56 | 755 | -0.73 | 273 | 115 | 40 | 3.6 |
| SANA | Sanaga | 23.52 | 1955 | -1.40 | 1979 | 133 | 42 | 5.1 |
| SEIN | Seine | 10.16 | 837 | -0.46 | 341 | 86 | 41 | 16.6 |
| SENG | Senegal | 28.46 | 710 | -0.91 | 706 | 435 | 146 | 6.4 |
| SEPK | Sepik | 23.12 | 3106 | 0.04 | 3834 | 73 | 23 | 1.1 |
| SJNA | St. John (North America) | 4.08 | 1168 | -0.14 | 981 | 48 | 23 | 0.4 |
| SJUA | San Juan | 25.12 | 2489 | -0.01 | 398 | 42 | 11 | 3.5 |
| SLAW | St. Lawrence | 5.70 | 990 | 0.02 | 7288 | 1058 | 485 | 48.6 |
| STKN | Stikine | -1.84 | 1161 | 0.25 | 1636 | 51 | 32 | <0.1 |
| TAGU | Tagus (Tejo) | 14.75 | 864 | -0.20 | 296 | 78 | 32 | 9.5 |
| TAKU | Taku | -1.68 | 1587 | 0.51 | 392 | 18 | 11 | <0.1 |
| TANA | Tana | -2.21 | 522 | 0.41 | 170 | 16 | 15 | <0.1 |
| TIGR | Tigris-Euphrates (Shatt al Arab) | 18.49 | 563 | -0.35 | 1073 | 789 | 314 | 63.9 |
| THUK | Tugela | 15.09 | 1047 | -0.77 | 86 | 33 | 11 | 2.3 |
| TULM | Tuloma | -1.23 | 616 | 0.54 | 46 | 26 | 24 | 0.2 |
| VOLT | Volta | 27.40 | 1147 | -0.87 | 1057 | 411 | 134 | 24.0 |
| VSTL | Vistula (Wista) | 7.50 | 735 | -0.75 | 1047 | 195 | 100 | 23.1 |
| VUKS | Vuoksa | 2.58 | 737 | 0.31 | 590 | 63 | 48 | 0.7 |
| YALU | Yalu | 4.44 | 884 | -1.16 | 155 | 51 | 22 | 5.4 |
| YAQU | Yaqui | 19.12 | 942 | 0.13 | 78 | 75 | 27 | 0.7 |
| YNSY | Yenisey | -5.24 | 525 | -0.11 | 18473 | 2571 | 1588 | 7.9 |
| YUKN | Yukon | -5.82 | 593 | -0.27 | 6374 | 835 | 624 | 0.1 |
| ZAMB | Zambezi | 21.58 | 992 | -0.66 | 3157 | 1380 | 464 | 38.2 |
| Standard deviation | | 9.60 | 707 | 0.43 | 19876 | 1023 | 413 | 81.1 |

*Drainage area calculated in ESRI ArcGIS from polygon outlines in the TFDD spatial dataset.

**Table A3: Details of specifications.**

| | (1) Dispute | (2) Cooperation | (3) Dispute | (4) Cooperation | (5) Dispute | (6) Cooperation | (7) Dispute | (8) Cooperation | (9) Dispute | (10) Cooperation | (11) Dispute | (12) Cooperation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Precipitation | 3.591** | -0.448 | 3.925** | 0.0212 | 6.064*** | -0.0904 | 4.097*** | 0.219 | 6.693*** | -1.617 | 4.040*** | -0.0838 |
| | (1.621) | (0.586) | (1.553) | (0.616) | (1.969) | (0.586) | (1.477) | (0.625) | (2.289) | (1.105) | (1.561) | (0.628) |
| Discharge | -0.0378 | 0.0860* | -0.0456 | 0.0844* | -0.0949 | 0.0237 | -0.0393 | 0.0712 | -0.0174 | 0.118** | -0.0512 | 0.0816 |
| | (0.133) | (0.0496) | (0.135) | (0.0484) | (0.128) | (0.0438) | (0.139) | (0.0519) | (0.133) | (0.0496) | (0.138) | (0.0503) |
| Temperature | 0.0233 | 0.315*** | -0.0664 | 0.245** | 0.00383 | 0.164** | -0.133 | 0.254** | -0.214 | 0.333*** | -0.660 | 0.247** |
| | (0.129) | (0.0960) | (0.120) | (0.0979) | (0.0951) | (0.0830) | (0.138) | (0.105) | (0.235) | (0.128) | (0.121) | (0.0978) |
| $Precipitation^2$ | | | | | | | | | -1.854*** | 0.768** | | |
| | | | | | | | | | (0.719) | (0.391) | | |
| $Drought^2$ | | | | | | | | | 0.0179 | 0.0213 | | |
| | | | | | | | | | (0.0388) | (0.0134) | | |
| $Temperature^2$ | | | | | | | | | 0.00649 | -0.00308 | | |
| | | | | | | | | | (0.00737) | (0.00556) | | |
| Discharge | | | | | | | | | | | 0.0038 | 0.0029 |
| | | | | | | | | | | | (0.004) | (0.0023) |
| Constant | -0.697 | -5.675** | 4.832 | -0.336 | 1.417 | -3.894** | 4.719 | -0.404 | 5.372 | -0.0395 | 4.656 | -0.459 |
| | (2.910) | (2.878) | (3.038) | (2.893) | (2.062) | (1.898) | (3.652) | (3.637) | (3.485) | (2.990) | (3.056) | (2.949) |
| Observations | 4,603 | 4,603 | 4,603 | 4,603 | 4,603 | 4,603 | 4,520 | 4,520 | 4,603 | 4,603 | 4,603 | 4,603 |
| Time Fixed Effects | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Lags | 1 | 1 | 1 | 1 | 0 | 0 | 2 | 2 | 1 | 1 | 1 | 1 |
| Quadratic Terms | No | No | No | No | No | No | No | No | Yes | Yes | No | No |

Standard errors clustered on the basin level in parentheses, *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Baseline outcome is cooperation. Odd (even) numbered columns show coefficients associated with dispute (cooperation). Columns 1 and 2 show estimate of specification A3 with no time fixed effects. Column 3 and 4 are our baseline specification. Columns 5 and 6 have no lags of climate variables while columns 7 and 8 have two. Column 9 and 10 show a quadratic specification while columns 11 and 12 show the result when discharge is added.