Basins at Risk –

Predicting International River Basin Conflict and Cooperation

Thomas Bernauer[a] *and Tobias Böhmelt*[b]

[a] ETH Zurich
Haldeneggsteig 4, 8092 Zurich, Switzerland
Phone: +41 44 632 67 71
Fax: +41 44 632 12 89
E-mail: thbe0520@ethz.ch

[b] University of Essex
Wivenhoe Park, Colchester CO4 3SQ, United Kingdom
Phone: +44 1206 87 2288
Fax: +44 1206 87 3234
E-mail: tbohmelt@essex.ac.uk

ETH Zurich
Haldeneggsteig 4, 8092 Zurich, Switzerland
Phone: +41 44 632 93 42
Fax: +41 44 632 12 89
E-mail: tobias.boehmelt@ir.gess.ethz.ch

Abstract: Growing demands for water combined with supply constraints may lead to an increased potential for *international* water conflicts, because many of the world's freshwater systems cut across national boundaries. Which international river basins are likely to experience greater conflict risks or, conversely, more cooperation? What are the factors that increase or decrease conflict risk (cooperation)? We use prediction and forecasting approaches to address these questions and compare the results with findings of an earlier "basins at risk" study. Whereas the earlier study identified twenty-nine basins at risk, our study identifies forty-four such river basins. It also arrives at different findings with respect to key determinants of river basin conflict and cooperation. The proposed analytical approach can help to increase the robustness of explanatory models, also in other areas of environmental politics. It could also make research findings more policy-relevant by moving from *ex-post* analysis to in-sample prediction and out-of-sample forecasting.

Keywords: Conflict; Cooperation; Prediction; Forecasting; International River Basins; Water

Acknowledgements: We thank the editorial team of *Global Environmental Politics* and four anonymous reviewers for very helpful comments. An online appendix, the data, and the replication files referred to in the text can be obtained from the authors on request and at http://www.ib.ethz.ch/research/data.

Thomas Bernauer is a Professor of Political Science at ETH Zurich, based at ETH's *Center for Comparative and International Studies* (CIS) and its *Institute for Environmental Decisions* (IED).

Tobias Böhmelt is a Lecturer in the Department of Government at the University of Essex and a Research Associate of ETH Zurich, based at ETH's *Center for Comparative and International Studies* (CIS) and its *Institute for Environmental Decisions* (IED).

Basins at Risk –
Predicting International River Basin Conflict and Cooperation

The existing literature identifies several factors that may influence conflict and cooperation in international river basins. It offers theoretical arguments to that end, and it empirically tests these arguments by means of qualitative case studies and large-*N* statistical work.[1] Empirical testing in this research is primarily of an *ex-post* nature, however. That is, it seeks to account for incidences or levels of international river basin conflict and cooperation observed in the past.

In this paper, we seek to take research one step further by moving from *ex-post* empirical analysis to *predictions* and *forecasts*. Predictions are "conditional statements about a phenomenon for which the researcher actually has data, i.e., the outcome variable has been observed."[2] A forecast "is a conditional statement about how a phenomenon will develop in the future and/or whose values are truly unknown."[3] Our motivation is substantive and practical, but also methodological. As it will become evident in the course of this analysis, *ex-post* empirical results, for example in the form of regression coefficients in quantitative studies on river basin conflict and cooperation, may not tell us much about the actual influence of specific explanatory variables, such as political system characteristics, water scarcity, or river geography. As noted by Ward et al., "policy prescriptions cannot be based on statistical summaries of probabilistic models."[4]

Moving from *ex-post* empirical analysis to prediction/forecasting thus serves two purposes. First, it complements the former by allowing us to discriminate among explanatory factors

[1] For example, Wolf et al. 1999; 2003a; 2003b; Dinar and Dinar 2003; Yoffe et al. 2003; 2004; Espey and Towfique 2004; Furlong et al. 2006; Gleditsch et al. 2006; Hensel et al. 2008; Zeitoun and Mirumachi 2008; Brochmann and Hensel 2009; Gerlak and Grant 2009; Stinnett and Tir 2009; Tir and Ackermann 2009; Zawahri and Gerlak 2009; De Stefano et al. 2010; Dinar et al. 2010; Zeitoun et al. 2010; Zawahri and Mitchell 2011; Brochmann 2012; Brochmann and Gleditsch 2012. For a recent overview, see, e.g., Bernauer and Kalbhenn 2010.

[2] Bechtel and Leuffen 2010, 311.

[3] Bechtel and Leuffen 2010, 309f.

[4] Ward et al. 2010, 364.

according to their predictive power. Second, it offers a more solid scientific basis for forward-looking (*ex-ante*) analysis, which is highly relevant from a policy perspective.

The most explicit forward-looking analysis of international river basin conflict and cooperation to date is the "basins at risk" study by Yoffe et al.[5] This article, which was published about ten years ago, relied on the Transboundary Freshwater Dispute Database (TFDD).[6] The TFDD codes water-related events (conflict and cooperation) in most international river basins on a continuum, the Basins at Risk (BAR) scale, which ranges from highly conflictive to highly cooperative events. Yoffe et al. correlated this scale with a large set of variables that might influence conflict risk or the chances of cooperation. Ultimately, and based on simple bivariate regressions and descriptive analysis, they identified those international river basins that appeared particularly risk-prone according to their analysis. On these grounds, Yoffe et al. placed river basins into three categories: (a) basins in which water conflict was already manifest; (b) basins in which conflict is possible in the future and for which there is evidence of existing tensions; and (c) basins in which conflict is possible in the future, but there is no present evidence of existing tensions. Table 1 aggregates these categories and summarizes the rivers Yoffe et al. predicted as "being at risk."[7]

Table 1

Prediction and forecasting require a robust *ex-post* empirical foundation. The Yoffe et al. study was in this respect ahead of its time, since large-*N* research on international river basin conflict and cooperation was not well developed in 2003, and made major progress only in recent years. Consequently, from today's perspective, the risk-profiling part in Yoffe et al. was not based on a sufficiently robust *ex-post* explanation of river basin conflict and

[5] Yoffe et al. 2003; see also 2004; Wolf et al. 1999; 2003a; 2003b.
[6] Wolf et al. 1999; 2003a; 2003b.
[7] Yoffe et al. 2003, 1123.

cooperation. Interestingly, however, quantitative studies on international basins in the past ten years have not made much use of advanced prediction and forecasting techniques. While the literature frequently cites Yoffe et al.'s work, it has not advanced the most policy-relevant part of that research agenda, namely the forward-looking risk-profiling component.

This paper systematically connects *ex-post* empirical analysis and the "basins at risk" agenda. Building on recent theoretical and empirical research, we first construct an *ex-post* explanatory model. We then use prediction and forecasting methods to evaluate the predictive power of particular explanatory factors and identify river basins that are prone to conflict or cooperation. The paper mirrors thus starts with a brief review of the existing literature and then describes how we move from *ex-post* statistical inference to prediction and forecasting. Afterwards, we discuss the results, while the conclusion compares the findings with the starting point for our work, the original "basins at risk" study.

Whereas the earlier research identified twenty-nine basins at risk, our study classifies forty-four such river basins. We also arrive at different findings with respect to key determinants of river basin conflict and cooperation. The analytical approach in this paper can help increase the robustness of explanatory models in other areas of international environmental politics, and make their findings more policy-relevant by moving from *ex-post* analysis to in-sample prediction and to out-of-sample forecasting.

Explaining International River Basin Conflict and Cooperation

We start by briefly presenting the existing literature's theoretical arguments and findings. This literature has been cumulative in nature, allowing us to be very selective as we focus on a set of recent quantitative studies.[8] This approach ensures that we use a broad theoretical framework for our research and also establishes the empirical base that we employ for our predictions and forecasts. Existing explanatory models rely either on traditional models of

[8] For a comprehensive review, see Bernauer and Kalbhenn 2010.

conflict, such as the gravity model,[9] or use variables that largely belong to three general clusters: (a) realist variables capturing state interests and the distribution of power; (b) liberal variables and transaction costs; and (c) river-specific and geographic variables.[10]

Brochmann and Gleditsch, building on Toset et al., Furlong et al., Gleditsch et al., and Owen et al.,[11] apply the gravity model. According to this model, conflict over river basins is likely to be driven by country size (population) and power (GDP per capita), and is inversely proportional to the distance between states (state contiguity and capital-to-capital distance).[12] Most of these variables are also considered in Yoffe et al.[13] Brochmann and Gleditsch find that the gravity variables affect conflict risk in the expected ways. Other explanatory variables, such as the size of a basin, political regime type (democracy), and river geography (upstream/downstream configurations) have also significant effects.

While it seems more common to focus on conflictive interactions between states and to infer that the absence of conflict constitutes cooperation,[14] some noteworthy exceptions have focused directly on cooperation. Zawahri and Mitchell,[15] for example, measure basin cooperation in terms of treaties between riparian country dyads. To explain cooperation, they use proxies for state interests, notably the share of a country's surface area in an international river basin, the ratio of external to internal sources of freshwater, and precipitation levels. The distribution of power is measured by upstream and downstream countries' economic and military capabilities. Liberal arguments are captured by the democratic form of government,[16] and by the similarity of domestic legal traditions in a riparian dyad. The explanatory model also includes the total number of states in a basin and a measure of geographic contiguity.

---

[9] Toset et al. 2000; Furlong et al. 2006; Gleditsch et al. 2006; Brochmann and Gleditsch 2012.

[10] Dinar and Dinar 2003; Yoffe et al. 2003; Hensel et al. 2008; Stinnett and Tir 2009; Tir and Ackermann 2009; Dinar et al. 2010; Zeitoun et al. 2010; Zawahri and Mitchell 2011; Brochmann 2012; Brochmann and Gleditsch 2012.

[11] Brochmann and Gleditsch 2012, 521; Toset et al. 2000; Furlong et al. 2006; Gleditsch et al. 2006, Owen et al. 2004.

[12] Brochmann and Gleditsch 2012, 522.

[13] Yoffe et al. 2003.

[14] See Brochmann 2012.

[15] Zawahri and Mitchell 2011.

[16] Marshall and Jaggers 2004.

Zawahri and Mitchell find that stronger dependence on freshwater resources makes cooperation more likely, while higher precipitation levels have the opposite effect. Furthermore, cooperation is more likely between democratic riparians, states with similar legal systems, and contiguous countries.

Kalbhenn focuses on liberal arguments, conceptualized by political regime type and linkages between states.[17] She argues that joint democracy increases trust and thus promotes cooperation between riparians. Moreover, trade relations and joint memberships in international organizations should be conducive to river cooperation. Kalbhenn's empirical analysis, which uses the same event data for river basin conflict and cooperation that we employ, supports these arguments. In line with earlier research, the analysis also includes river characteristics, realist variables, and variables for the gravity model.[18]

Brochmann addresses a similar research question as Kalbhenn.[19] Her research focuses on all international river basins between 1948 and 1999, using the TFDD data.[20] In terms of the explanatory variables, Brochmann argues that realist variables, such as peace years, alliances, and state power are likely to affect river cooperation. Her model also includes variables mirroring Kalbhenn's liberal approach as well as indicators that capture river-specific characteristics.[21]

Based on the existing literature, as briefly reviewed here, we identified sixteen variables that are commonly used in models of international river basin conflict and cooperation. The appendix summarizes these variables, points to the underlying theoretical rationales, and refers to the data sources.[22] We construct an explanatory model including these variables as the starting point for predicting and forecasting basin conflict and cooperation.

---

[17] Kalbhenn 2011.
[18] Kalbhenn 2011, 719ff.
[19] Brochmann 2012; Kalbhenn 2011.
[20] Wolf et al. 1999; 2003a; 2003b.
[21] Brochmann 2012, 152.
[22] Some studies also use variables for trade dependence and international non-governmental organizations. We omit these items due to the limited availability of data. See also Yoffe et al. 2003, 1116.

From Statistical Inference to Prediction and Forecasting

As noted in the preceding section, empirical studies have shown that the explanatory variables we discussed (and as summarized in the appendix) have significant effects on international river basin conflict and cooperation. Several scholars contributing to the more general literature on conflict and cooperation argue, however, that drawing inferences from statistically significant results can be misleading to the extent that those inferences are unlikely to tell us much about the predictive power of a specific covariate or an entire model: statistically significant results may improve our understanding of the relationship between variables in a given sample under study, but they may not provide information on the exact same relationship in another sample of data.[23] Yoffe et al. are at least discreetly aware of this limitation when stating that "[c]ategorizing a basin at risk does not presume to identify basins in which acute conflict will occur, but to point to basins worth more detailed investigation."[24]

We submit that moving from *ex-post* statistical inference to in-sample prediction and out-of-sample forecasting can help improve the explanatory power of our models. Moreover, it makes research more policy relevant, because policymakers are usually not only interested in why conflict or cooperation took place in the past, but also what the future might bring. In more technical terms, as noted by Ward et al.,[25] "it is quite possible to focus on statistically significant results that are artifacts in the sense that they do not generalize beyond the specific cases studied. This happens if we focus only on statistically significant relationships and may actually hinder our ability to generalize to out-of-sample situations, such as the future!"

Accordingly, we examine (a) the predictive power of those explanatory variables we discussed (and as summarized in the appendix) using in-sample prediction techniques and (b)

---

[23] For example, Ward et al. 2010; Gleditsch and Ward 2013.
[24] Yoffe et al. 2003,1123.
[25] Ward et al. 2010, 364.

the ability of these variables to forecast basins at risk and those that are likely to see cooperation using out-of-sample approaches.[26]

In-Sample Prediction: Assessing Predictive Power with "Existing Data"

For our empirical work, we follow other studies[27] and opt for the dyad-basin-year as the unit of analysis. The dependent variables measure international river basin conflict or cooperation, based on the International Rivers Cooperation and Conflict event data (IRCC) compiled by Kalbhenn and Bernauer for 1997-2007.[28]

The rationale behind choosing these data is twofold. First, the IRCC data are coded from a uniform set of information sources. While the TFDD offers data for a longer time period than the IRCC, the main reason for using the IRCC instead of the TFDD is that major changes in the availability of news media texts over time (notably the advent of the digital revolution) make it problematic to use event data coded from partly changing sources for a very long period of time (as it is the case for the TFDD). Second, the IRCC data were coded and are publicly available in a format that is easier to use for an advanced statistical analysis of river basin conflict and cooperation than the TFDD.

Ultimately, using the IRCC event data appears most appropriate in view of the outcome we want to explain: conflictive and cooperative water-related events in international river basins. Applying our analytical approach to other types of dependent variables that have been used in the literature, for instance river treaties, river claims, or militarized interstate disputes, would be straightforward and certainly useful. However, implementing our analysis for different types of dependent variables within this paper is prevented due to space constraints. Table 2 provides an overview of the IRCC scale.

[26] Ward et al. 2010; see also Gleditsch and Ward 2013; Bechtel and Leuffen 2010.
[27] For example, Zawahri and Mitchell 2011; Kalbhenn 2011; Brochmann 2012.
[28] Kalbhenn and Bernauer 2012; see also Kalbhenn 2011.

Table 2

At this point, it should be noted that international river basin conflict can, according to the IRCC coding rules, include “water wars,” e.g., interstate disputes over water resources. Yet, there is not a single event in the IRCC data that is coded as a -6 value and, thus, all observed and recorded events have the character of international political disputes, low-intensity violent actions, or international cooperative events. Similarly, however, neither the TFDD nor the Issue Correlates of War Project (ICOW)[29] include events that would qualify as a “water war.”

We now continue by examining the in-sample and out-of-sample predictive power (a) of two comprehensive models on river basin conflict and cooperation; (b) of the single predictors in these models; and (c) by identifying those basins that are most likely to be at risk or to experience cooperation in the future. Thus, after estimating the *ex-post* statistical models that are based on the IRCC data and the explanatory factors introduced above, we move beyond such approaches, which rely exclusively on the statistical significance of explanatory variables. To this end, we aggregated the IRCC data, which record individual events, to the dyad-basin-year, and generated two binary variables for conflict and cooperation that serve as our dependent variables. The first binary variable (*Conflict*) receives a value of 1 if the median IRCC score for a dyad-basin-year is negative (0 otherwise); the second variable (*Cooperation*) receives a value of 1 if the median IRCC score is positive (0 otherwise).[30] Consequently, we estimate two separate models: one for conflict (Model 1) and one for cooperation (Model 2). Next to the explanatory variables we discussed (and as summarized in the appendix), these models incorporate a conflict-years variable and a cooperation-years

[29] Wolf et al. 1999; 2003a; 2003b; Hensel et al. 2008.
[30] For the same or similar approaches, see, e.g., Kalbhenn 2011; Brochmann 2012; Gleditsch and Ward 2013.

variable, respectively, as well as different sets of cubic splines to correct for temporal dependencies.[31]

We considered, but did not use two alternative empirical measures for the dependent variable. First, one could argue in favor of the yearly mean value for the dyad-basin-year before calculating the binary dependent variables. However, the mean is more sensitive to extreme values than the median, which could bias the results.[32] Second, one could change the unit of analysis and compare individual events. While this would circumvent the issue of using either the mean or median for aggregation, it increases the number of observations substantially and, from our point of view, artificially as all of our covariates are measured at the country-dyad or the river basin level. In other words, using the dyad-basin-year as the unit of analysis avoids inflating the number of observations, but requires data aggregation either in terms of the mean or median – and we believe that the median is likely to be the more accurate choice.

Due to the temporal scope of the IRCC dataset and because of data limitations for our explanatory variables, Models 1 and 2 cover the time period from 1997 to 2004, i.e., the period for which both the IRCC data and our explanatory variable) consistently provide information. While this temporal limitation might appear as a shortcoming of our research at first sight, it offers noticeable opportunities for the out-of-sample forecasts: we can use the models for 1997-2004 to forecast river conflict and cooperation in 2005-2007. Afterwards, we can compare those out-of-sample predictions with the empirically observed values on the dependent variables for the latter period in order to assess the models' forecasting capabilities. Our results of the *ex-post* models are summarized in Table 3.

Table 3

---

[31] Beck et al. 1998.
[32] Kalbhenn 2011.

Since our main interest is in prediction and forecasting, we discuss this table's results only briefly. In Model 2, for example, more water dependence is associated with more cooperation. Conversely, we might expect a negative coefficient for the water dependence variable in Model 1. This coefficient is neither negative nor significant, however. In contrast to some other studies, democracy reduces the probability of cooperation (Model 2). The similarity of the legal system has a significantly negative effect on conflict risk, but also on cooperation. The findings for the number of riparian states and membership in international organizations are similar to what other scholars found.[33] It is important to note, however, that dependent variables and time periods differ across studies. Hence, our initial findings should not be viewed as an empirical contest between models, data, or samples, but rather as a plausibility check of our empirical setup. Either way, predictions and forecasts, which we now turn to, are "beyond the issue of the sign and significance of particular coefficients."[34]

The application of in-sample predictions is straightforward. First, we use the models in Table 3 to estimate the predicted probabilities of conflict and cooperation, respectively, for each dyad-basin-year. The predicted probabilities can vary between 0 (0 percent) and 1 (100 percent), and we group these into quintiles, which we compare with the actual instances of conflictive or cooperative dyad-basin-years in our data. For these calculations, we refer to the fifth, fourth, and third quintile as the "most-likely" group, i.e., those groups of predicted probabilities that are most likely to match with the actual instances of conflictive or cooperative dyad-basin-years. The first and the second quintile, in contrast, are the "least-likely" group, which is equivalent to those groups of predicted probabilities that are comparatively low and, thus, less likely to correctly predict observed onsets of conflict or cooperation. The findings are summarized in Table 4 and Figure 1.

---

[33] For example, Kalbhenn 2011; Brochmann 2012.
[34] Gleditsch and Ward 2013, 23.

Table 4 and Figure 1

The most-likely group for Model 1 includes twenty-seven out of thirty-one conflictive dyad-basin-years in our data (87 percent). With regard to Model 2, 416 out of 445 (93 percent) cooperative dyad-basin-years are placed in the most-likely group. In other words, only four dyad-basin-years that were *de facto* conflictive are characterized as least-likely cases. Similarly, only twenty-nine out of 445 cooperative dyad-basin-years are classified as non-cooperative, although they were in fact cooperative.

Figure 2 sheds more light on the in-sample predictive power of Models 1-2. The Receiver Operator Characteristic (ROC) plot shows the extent to which models with more predictive power generate "true positives at the expense of fewer false positives."[35] Thus, a perfectly predictive model would correctly classify all empirically observed cooperative or conflictive dyad-basin-years and never generate false positives, i.e., dyad-basin-years that were not conflictive or cooperative, although our estimations predict the opposite. The importance of the ROC plot is highlighted by Gleditsch and Ward:[36] any "threshold for considering an event as predicted could be seen as an arbitrary description of the continuous distribution of the probabilities." Hence, despite our careful selection of the thresholds for the most-likely and the least-likely groups above, this argument by Gleditsch and Ward clarifies why the ROC curves approach is more precise in showing the predictive power of models. Figure 2 emphasizes that although our models do not perfectly predict either river conflict or cooperation, these models yield a higher predicted probability for a randomly chosen event than for a randomly chosen non-event. This finding is reflected in the ROC curve statistic (AUC), which theoretically varies between 0.50 (no predictive power) and 1.00 (perfect

---

[35] Ward et al. 2010, 366.
[36] Gleditsch and Ward 2013, 23.

predictive power). As demonstrated by Figure 2, our models perform well above average in this regard: Model 1 has an AUC value of 0.78 and Model 2 has an AUC statistic of 0.82.

Figure 2

Out-of-Sample Forecasting Using "New Data"

The previous section leaves us with the question of how the predictive power of our models and their individual covariates looks like when moving to the "harder" test of an out-of-sample forecast, i.e., what is the predictive power when trying to correctly predict outcomes that are not "within the very same set of data that was used to generate the models in the first place."[37]

Our first step in this section is a so-called 4-fold cross-validation setup[38] – for the full models and for models that omit one or some of the explanatory variables from the estimation. This approach divides the existing data into four subsets, while the dyad-basin-year observations are randomly assigned to these four different sets. All except one of the four subsets are then pooled together and this pooled set of observations is used to estimate the models shown in Table 3. The remaining subset, also called the "test set,"[39] which we do not use for the pooled set of observations and the initial model estimation, then serves to assess the predictive power of the model estimated for the pooled subsets. Put differently, we try to predict the outcome variables of the test set with models that are based on the pooled set of observations, which were randomly assigned to this. Afterwards, we calculate the AUC for

[37] Ward et al. 2010, 370.
[38] See Ward et al. 2010, 370 for a more detailed description of this approach.
[39] Ward et al. 2010, 370.

measuring the predictive power.[40] We repeat this procedure ten times and then present the mean AUC for several model constellations in Figures 3 and 4.

Figures 3 and 4 show the results (AUC values on the vertical axis) for the full models as specified in Table 3 and models in which certain explanatory variables are omitted (labeled as stages on the horizontal axis). The values presented in the first stage of either Figure 3 or 4 indicate the AUC of the full model that leaves out one covariate at a time. Lower values than the value of the "Full Model stage" indicate that a covariate contributes to the out-of-sample prediction power of the model. Higher values than the AUC from the full model indicate that including a specific covariate reduces the forecasting capability of the model. Hence, predictors associated with *lower* values have a *higher* power for forecasts. After completing the calculations for the first stage, we then identified the strongest predictor (label underlined) and constantly left it out for the second stage (and the third stage), while repeating the calculations for all other covariates again. On this basis, we identified the three strongest single predictors for river conflict and cooperation. The reason for this is that demonstrating that an entire model or its alternative specifications perform above the AUC level of 0.50 does not allow for firm conclusions concerning the forecasting power of individual covariates. We thus follow Ward et al.[41] and estimate the AUC for each model, dropping covariates one after the other.

Figure 3 and Figure 4

The forecasting power as measured by the AUC value both of the full models and the reduced models at the three stages, where we exclude an explanatory variable at a time, is generally lower for the 4-fold cross-validation than for the in-sample predictions. Nevertheless, the forecasting power of the full models remains reasonably high: we obtain a

[40] Ward et al. 2010, 370.
[41] Ward et al. 2010, 367.

score of 0.66 for conflictive dyad-basin-years and 0.80 in forecasting cooperative dyad-basin-years. These findings are driven by a small subset of variables for which the average AUC is lower than the AUC of the full model. For example, *Population, Small (log)* is the strongest predictor in the first stage of the conflict model. When dropping this variable, the out-of-sample predictive power decreases from an AUC of about 0.66 to 0.63 in the conflict model. Similarly, *Number of Riparian States* (decrease in AUC from 0.80 to about 0.79) is the strongest predictor at the first stage of the cooperation model. We then discard both these strongest predictors from the respective model for the second stage and repeat the procedure of a 4-fold cross-validation for all remaining explanatory variables. After identifying the strongest predictors in the second stage, we reiterate this procedure for a third stage. Our results show, therefore, that dropping some of the explanatory variables included in Table 3 from any model estimation would not only be misleading from the perspective of statistical significance, but also from the viewpoint of predictive power. However, this conclusion only applies to a small subset of covariates that contribute to the forecasting power of our models.

With regard to Figure 3, *Legal System Similarity*, *Downstream Power*, and *Population, Small (log)* contribute most to the out-of-sample power, i.e., they display a lower AUC than the full model when leaving these items out of the estimation for the first stage; for the second stage, the contributing covariates are *Precipitation, Downstream Power, Democracy, External Water Dependence*, and *Population, Large (log)*; for the third stage, only *Precipitation* contributes to the forecasting power of the conflict model. With regard to cooperation (Figure 4), the variables *Number of Riparian States, External Water Dependence*, and *Population, Small (log)* are the three strongest predictors. Most other variables contribute very little to the cooperation model's predictive power – *IGO Membership* being the most obvious covariate. Figures 3 and 4 also suggest that more parsimonious models can perform better in forecasting river basin conflict or cooperation than more complex models. Already (and only) the three strongest predictors for either conflict or cooperation seem to work very well in this respect.

Finally, in a last step to assess the forecasting power of our models, we again use the grouping of the predicted probabilities by quintiles and compare these with the empirically observed conflictive or cooperative dyad-basin-years. We used this approach already for Table 4 and Figure 1. The crucial difference between the models underlying Table 4/Figure 1 above and the models (not reported here) leading to Table 5/Figure below, however, is that we now use the covariate values in 2004 to predict river conflict and cooperation between 2005 and 2007. That is, we employ data for the explanatory variables in the last observed year (2004) and impute these into the years 2005-2007 to predict conflict or cooperation, as measured by our dichotomous dependent variables, in this period. This approach mirrors a true forecast to the extent we can make a conditional statement about how conflict and cooperation will develop in the future as we treat the dependent variables' values as unknown.[42] Again, we refer to the fifth, fourth, and third quintile as the most-likely group, while the first and the second quintile are designated as the least-likely group.

Table 5 and Figure 5

Based on this test, the most-likely group comprises thirteen out of thirteen conflictive dyad-basin-years in our data (100 percent). Slightly less accurately, 182 out of 188 dyad-basin-years (97 percent) are captured by the cooperative most-likely group. This means that, although we now use "new data," i.e., dyad-basin-years for the dependent variable that were originally not covered by the models in Table 3, the forecasting power in this case is higher relative to the in-sample predictions and the 4-fold cross-validation. This finding is upheld by the values of the ROC plots in Figure 6. The accuracy of the model for conflictive dyad-basin-years increases to 0.97, while the forecasting power of the cooperation model is 0.90.

[42] Bechtel and Leuffen 2010, 309f; see also Gleditsch and Ward 2013, 24f.

Figure 6

Basins at Risk – Revisited

The analysis shows that our models have the ability to produce accurate predictions and forecasts for conflictive and cooperative dyad-basin-years. This allows us now to return to our principal motivation and compare our findings with the basins at risk identified by Yoffe et al.[43] To this end and in our setup, a basin is predicted to be at risk (or to be characterized by cooperation) if at least 90 percent of all dyad-basin-years in both the in-sample and out-of-sample estimations are classified under the "most-likely groups" of conflict (or cooperation) introduced above. Table 6 summarizes the results.

Table 6

The first column mirrors Table 1. The second column lists all basins that appear in our in-sample and out-of-sample predictions or forecasts of conflict and fulfill the "90 percent threshold." Note that this second column lists forty-four basins as compared to twenty-nine in the first column. There is a rather limited overlap as only six basins appear in both lists: Asi/Orontes, Cross, Han, Indus, Ob, and Tigris-Euphrates. One of these six basins constitutes a particularly interesting case: the Cross River in Nigeria is predicted to be one of the most conflict-prone rivers according to our research and is also included in the list by Yoffe et al. However, the IRCC do not record any conflictive event in this basin, but only two neutral events involving consultations between riparian countries. Still, according to our work and Yoffe et al., conflict is likely to be dominant here.

[43] Yoffe et al. 2003.

With regard to the third column, we obtain evidence that it is worth studying river basin conflict and cooperation side-by-side.[44] This column shows that five basins, which are categorized as basins at risk by Yoffe et al., are predicted to have at least 90 percent of dyad-basin-years with a cooperative median according to our estimations: Indus, Jordan, Mekong, Nile, and Senegal. In addition, our work suggests that six more basins are likely to be cooperative also in the future. Particularly the Indus River, which is shared by India and Pakistan, is worth examining in more detail. While it is categorized as a basin at risk in the Yoffe et al. study, descriptive statistics for the IRCC data suggest the same: out of the forty-nine events coded in total between 1997 and 2007 for this basin, fourteen (29 percent) of those events are coded as conflictive. Note, however, that these descriptive statistics might be misleading. In fact, our in-sample and out-of-sample work suggests that we might observe more cooperative interactions in the future.

In other words, while our approach identifies some basins at risk that were also on the Yoffe et al. list, substantial differences appear. Assuming that the IRCC and the TFDD data cover the same underlying theoretical concepts,[45] the dissimilarities are probably caused by different methodological approaches. We believe that our approach leads to more accurate predictions, however. As stated above, bivariate regression models, which were used for the 2003 study, can produce information on statistical significance; but they cannot generate information on relationships between variables in other samples or with regard to the predictive/forecasting power.

Differences in methodology also result in differences concerning predictors. Yoffe et al. identified the following predictors to be most crucial: high population density, low GDP per capita, overall unfriendly relations between riparian countries, politically active minority groups, proposed large dams or other water development projects, and limited or no freshwater treaties. While some of these variables could not be included in our setup due to

[44] See also Zeitoun and Mirumachi 2008; Zeitoun et al. 2010.
[45] See Kalbhenn and Bernauer 2012.

limited data availability (e.g., politically active minority groups) or because they are already coded within the IRCC scale (e.g., water development projects and treaties), it is interesting that only the population variable – in our setup, *Population, Small (log)* – appears as a robust predictor for conflict (first stage in Figure 3) and cooperation (third stage in Figure 4). GDP per capita, for example, which is identified by Yoffe et al. as an important predictor and is also frequently used in other studies examining states' river basin interactions[46] as well as studies of armed conflict,[47] is unlikely to help us in anticipating future river conflict or cooperation.

These differences notwithstanding, the majority of variables classified as strongest predictors in our models support other studies that emphasize river characteristics and water availability.[48] Other determinants, which are also frequently used in explanatory models of river conflict and cooperation, such as *IGO Membership* or *Democracy,* are unlikely to play a major role. Note, however, that the lack of predictive power for some of these variables that are seen as strong predictors in, e.g., studies on civil war, may be related to the absence of violent conflict in our data. The two GDP per capita variables or regime type are arguably the most prominent cases in this regard. That being said, civil war onset is a different outcome than conflict and cooperation over international river basins. Moreover, when confronting the statistical (*ex-post*) evidence for democracy with its prediction/forecasting power, Ward et al., for example, find that regime type is actually one of the weaker predictors.[49] The point that we are trying to make with this paper, in line with Ward et al.,[50] is that findings exclusively based on statistical (*ex-post*) evidence might be misleading, and that prediction and forecasting are more powerful tools in this respect.

[46] For example, Gleditsch et al. 2006; Stinnett and Tir 2009; Tir and Ackermann 2009; De Stefano et al. 2010; Dinar et al. 2010; Brochmann 2012; Brochmann and Gleditsch 2012.
[47] Ward et al. 2010; Gleditsch and Ward 2013.
[48] For example, Kalbhenn 2011; Zawahri and Mitchell 2011; Brochmann 2012; Brochmann and Gleditsch 2012.
[49] Ward et al. 2010.
[50] Ward et al. 2010.

Conclusion

The main purpose of this research was to put *ex-post* empirical models of international river basin conflict and cooperation to a harder test by examining their ability to predict and forecast variation on the outcome variable of interest. The empirical models we estimated perform well in the in-sample tests (1997-2004), the 4-fold cross-validation setup, and the out-of-sample forecast that allows for a comparison of predicted conflictive as well as cooperative dyad-basin-years with empirically observed cases (2005-2007).

The motivation for our research was the "basins at risk" study by Yoffe et al. This study received strong attention from policy and academic circles, but was somewhat ahead of its time because large-*N* research on international river basin conflict and cooperation as well as research on prediction and forecasting methods has made rapid progress only in recent years. The main contribution of our research is to augment the most advanced quantitative research on river basin conflict and cooperation with a prediction/forecasting approach, and to revisit the basins at risk issue. It has resulted in a substantially revised list of basins at risk and a set of predictors that is backed-up by more robust empirical evidence. While none of the river basins identified is likely to experience a "water war," our approach and its results will hopefully be useful for policymakers in terms of drawing their attention to basins that do or will require greater effort in conflict prevention and/or resolution.

The work reported in this paper leaves several opportunities for further research. First, case studies should focus in greater depth on individual river basins to re-examine some of our findings that may appear counterintuitive. Examples include the Cross River in Nigeria (see above) and the Aral Sea basin. The latter is listed as a basin at risk by Yoffe et al., but is not identified as conflict-prone by our in-sample and out-of-sample predictions for 1997-2007. However, it only drops out of our list, because it is just below the "90 percent conflictive dyad-basin-years threshold" in the out-of-sample predictions. Moreover, while our results suggest that that forty-four basins are at risk, the international community will be unable to alleviate the conflict potential in all those basins; in a related fashion, most of the conflicts are likely to be at a sufficiently low level, which the riparian countries might then be able to resolve themselves. Case studies could thus examine more thoroughly, which basins are likely to have conflicts that go beyond their own conflict resolution capacity, or why some basins experience both cooperation and conflict, within specific dyad-basin-years or over time, whereas others are dominated by one of the two interaction types.[51] The Indus River, briefly discussed above, is a good example.

Second, our approach reduces information on conflict and cooperation intensity to binary variables, whereas the IRCC scale ranges from -6 to +6. Since extremely conflictive or cooperative international water events are very rare, this approach is defensible.[52] Further research could explore alternatives to using the median value of the IRCC scale for dyad-basin-years as extreme conflictive or cooperative events might have been averaged out with our approach (in many cases potentially to 0).

Finally, future research could employ the prediction and forecasting approach to strengthen explanatory models of river basin conflict and cooperation using other outcome variables, e.g., militarized interstate disputes, river treaties, or alternative event data such as the TFDD. Such work could be linked to the broader literature on conflict and cooperation. Our approach might also be used for other questions of interest in research on international environmental politics, such as explaining variation in environmental performance across countries or participation rates in and compliance with global environmental agreements. Adding prediction and forecasting to standard empirical models would also make them more policy relevant, because policymakers are at least as curious as researchers with respect to future trends, developments, and outcomes.

---

[51] See also Zeitoun and Mirumachi 2008; Zeitoun et al. 2010.

[52] Kalbhenn and Bernauer 2012 identify 5,881 events in total. Out of these, only 77 events have an IRCC score of –3 or less (1.31 percent), and only ten events have a score of +5 or higher (0.17 percent).

Table 1
Basins at Risk in Yoffe et al. (2003)

River Name	River Name	River Name
Aral Sea	Jordan	Okavango
Asi/Orontes	Kune	Red
Ca	Kura-Araks	Saigon
Chiloango	La Plata	Salween
Cross	Lake Chad	Senegal
Drin	Lempa	Song Vam Co Dong
Ganges-Brahmaputra-Meghna	Limpopo	Tigris-Euphrates
Han	Mekong	Yalu
Indus	Nile	Zambezi
Irrawaddy	Ob	

Table 2
Overview of IRCC Scale

IRCC Value	*Coding Description*
+6	**Alliance –** ratification of freshwater treaty
+5	**Official support –** signing of freshwater treaty
+4	**Agreement/commitment** • Closing plant in own country that possibly leads to pollution in other country • Financial support for water projects in other country • Cooperative/joint water management (irrigation, water supply, etc.) projects
+3	**Agreement of low scale** • Meeting of environmental ministers/heads of states for talks on joint water issues • Drafting cooperation agreement/joint policy • Setting up expert group/commission (on joint water issues)
+2	**Verbal support** • Meeting of river commission with expression of policy goals • Invite inspectors from other country in order to dispel doubts on possible pollution, etc. • Expressing willingness to come to an agreement
+1	**Minor official exchanges, talks or policy expressions** • Meeting of high officials discussing joint water issues • Submitting position on joint water problem • Informing other country about environmental accidents
0	**Neutral acts** • Purely rhetorical statements
-1	**Mild verbal expressions displaying discord in interaction** • Proposing unwanted dam or other flow regulation • Refusing to accept compromise/solution to dispute proposed by other country • Failure to come to reach agreement in dispute settlement attempt
-2	**Strong verbal expressions displaying hostility in interaction** • Failure to report environmental accidents harmful to other country • Turning to court • Refusing participation in meetings/summits
-3	**Hostile actions** • Disposal of waste in shared water • Contamination of shared water • Abrogation of a water agreement
-4	**Breaking diplomatic relations** • Intended pollution • Unilateral construction of water projects against another country's protest • Reducing flow of water to another country
-5	**Any violent acts** (that do not constitute a war)
-6	**Formal declaration of war or militarized interstate disputes**

Source: Kalbhenn and Bernauer 2012.

Table 3
Logistic Regression Models

	Model 1 – Conflict	*Model 2 – Cooperation*
Territory in Basin	0.011	0.003
	(0.013)	(0.005)
External Water Dependence	0.003	0.014
	(0.010)	(0.003)***
Precipitation	-0.001	-0.001
	(0.001)	(0.001)
GDP per capita, Large (log)	0.098	-0.093
	(0.274)	(0.106)
GDP per capita, Small (log)	0.185	0.187
	(0.285)	(0.119)
Population, Large (log)	0.243	-0.006
	(0.247)	(0.074)
Population, Small (log)	0.649	0.268
	(0.183)***	(0.075)***
Democracy	-0.051	-0.037
	(0.034)	(0.014)***
Alliance	0.061	-0.220
	(0.337)	(0.141)
IGO Membership	-0.032	0.009
	(0.015)**	(0.006)
Legal System Similarity	-0.811	-0.632
	(0.409)**	(0.159)***
Distance (log)	-0.126	0.164
	(0.288)	(0.097)*
Contiguity		-0.207
		(0.162)
Number of Riparian States	0.020	0.121
	(0.073)	(0.015)***
Upstream Power	-6.978	-1.363
	(6.272)	(2.424)
Downstream Power	-18.665	-5.301
	(7.815)**	(3.492)
Years Variable	-0.748	-0.676
	(0.381)**	(0.101)***
Spline 1	-0.102	-0.250
	(0.092)	(0.404)
Spline 2	0.285	-0.010
	(0.366)	(0.042)
Spline 3	-0.528	0.613
	(0.730)	(1.063)
Observations	3035	3531
Log Pseudolikelihood	-150.69	-1062.50
Wald χ^2	91.50***	472.93***

Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; *Contiguity* dropped in Model 1 due to insufficient variance; constant included in both models but omitted for presentation.

Table 4
In-Sample Predictions

Quintile of Predicted Values	*Conflict (Model 1)*	*Cooperation (Model 2)*
Least-Likely Category (1-2)	4	29
Most-Likely Category (3-5)	27	416
Total	31	445

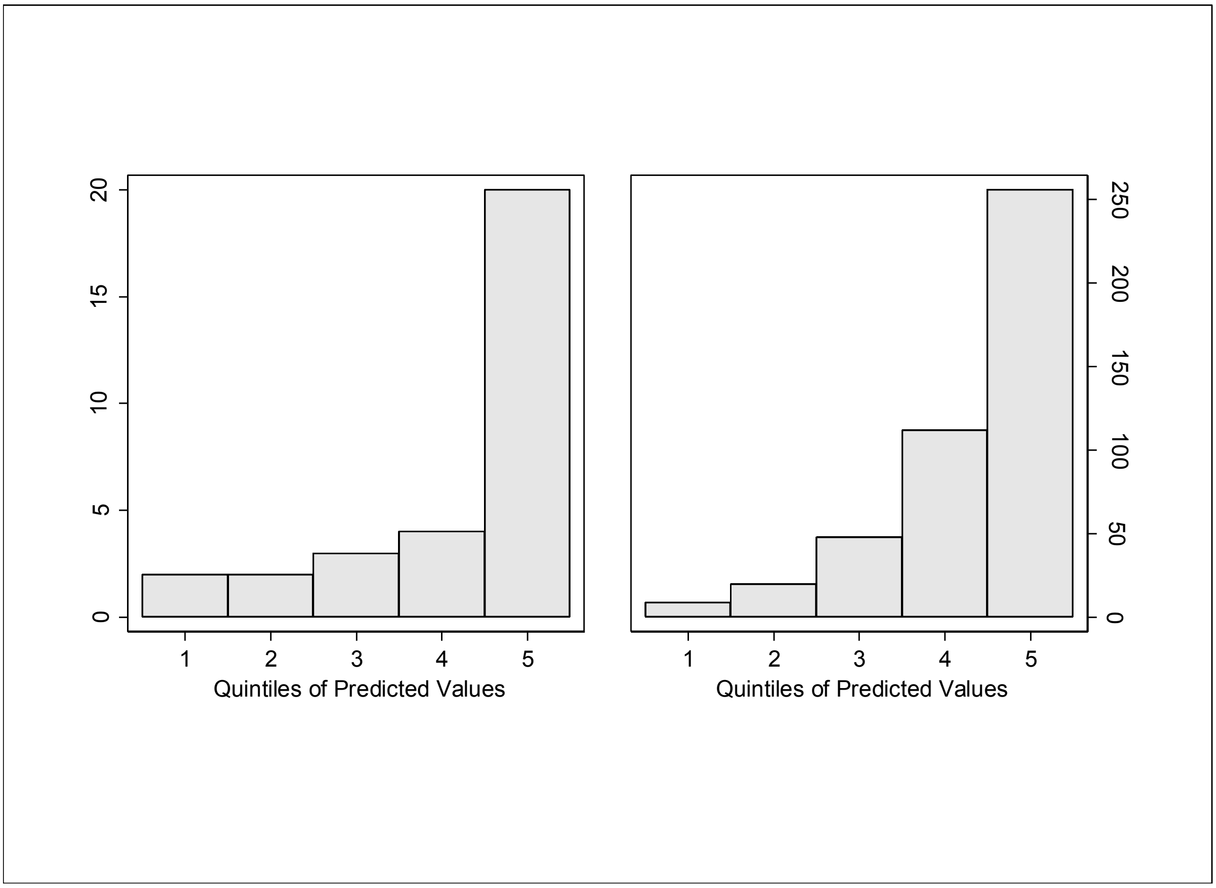

Figure 1.
In-Sample Predictions

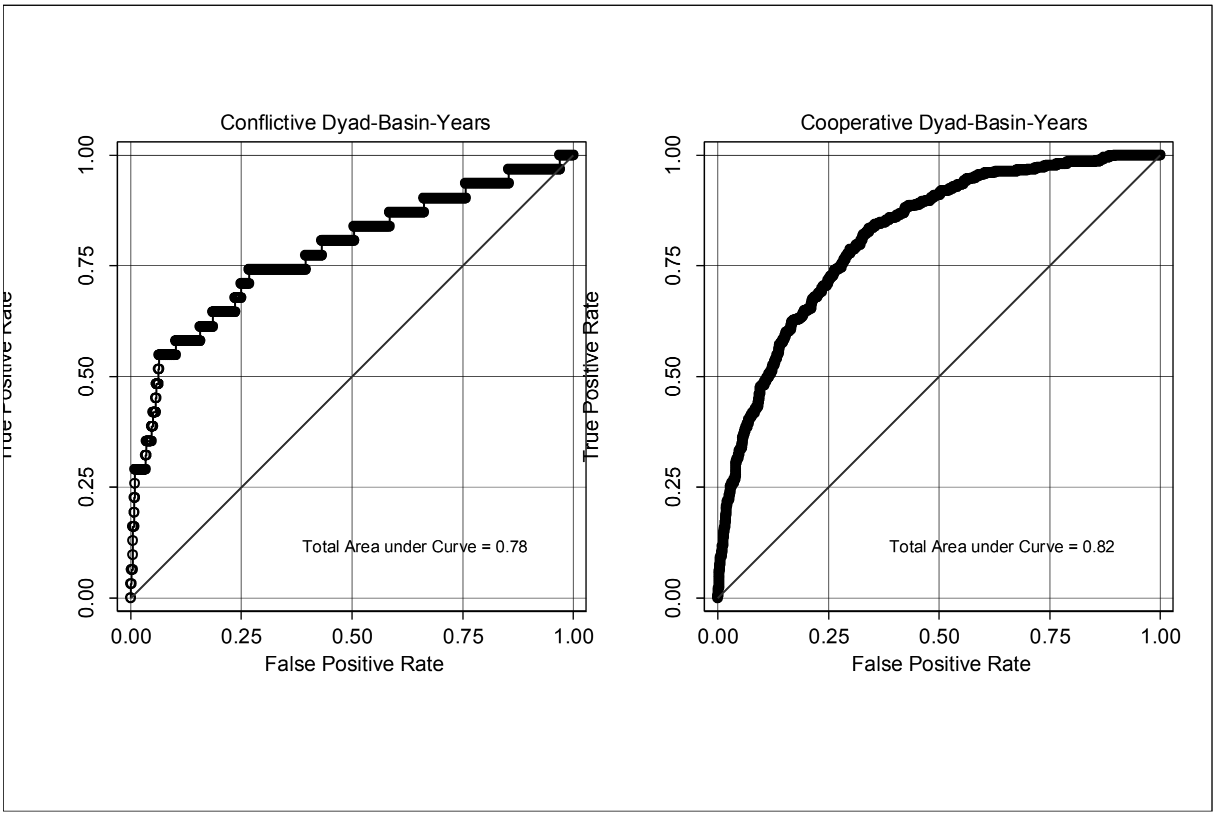

Figure 2.
In-Sample Predictions: ROC Plots

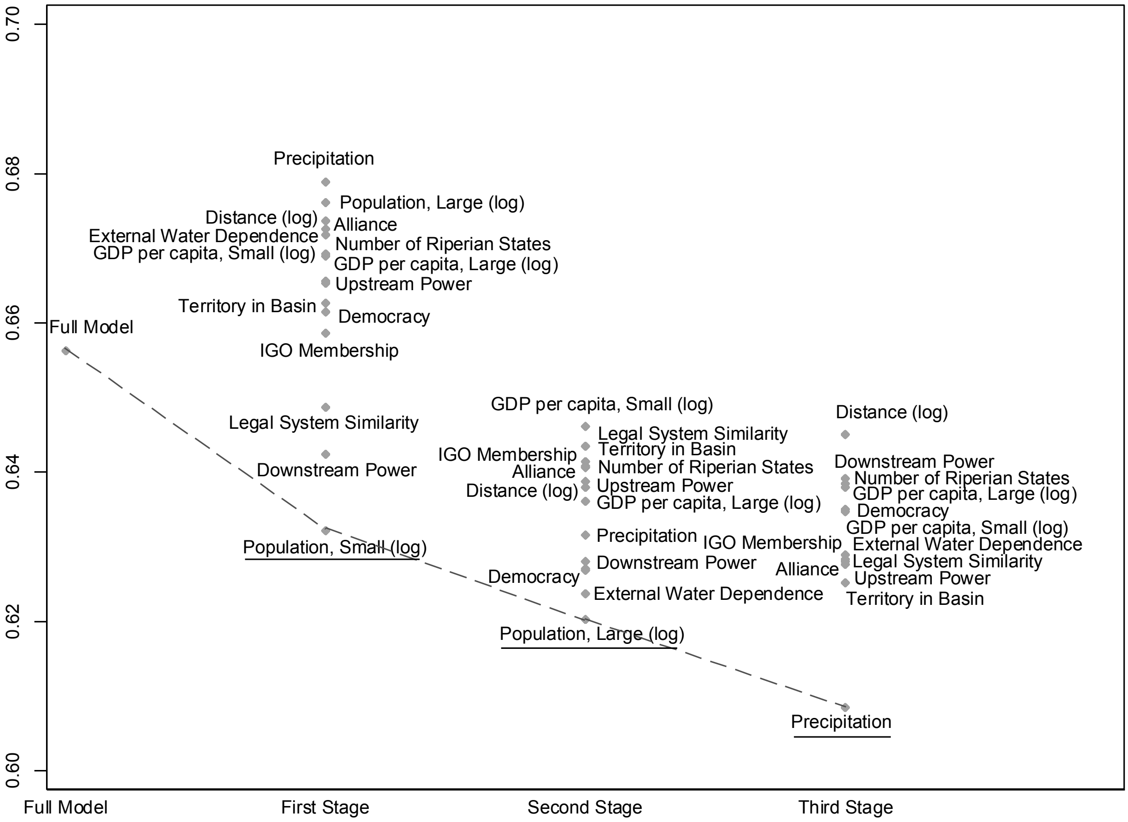

Figure 3.
Out-of-Sample Predictive Power: Conflict

Variable labels adjusted to prevent overplotting.

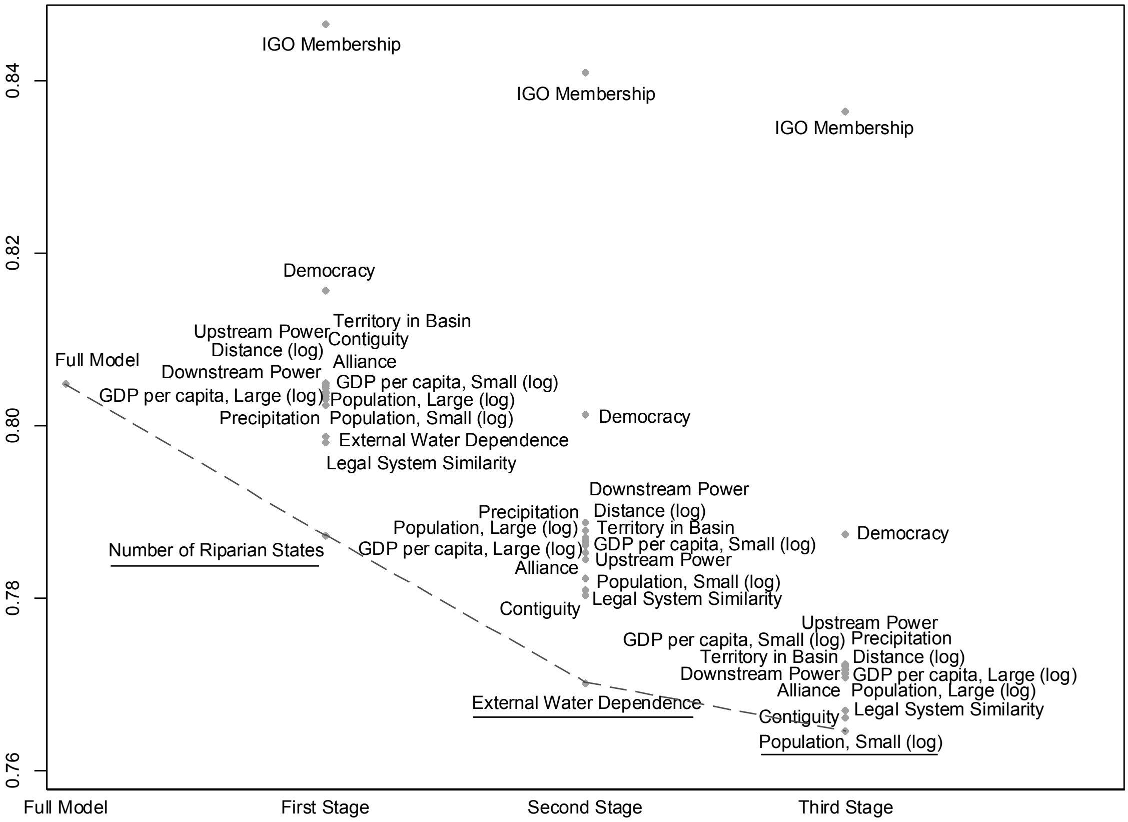

Figure 4.
Out-of-Sample Predictive Power: Cooperation

Variable labels adjusted to prevent overplotting.

Table 5
Out-of-Sample Predictions: Forecasting

Quintile of Predicted Values	Conflict	Cooperation
Least-Likely Category (1-2)	0	6
Most-Likely Category (3-5)	13	182
Total	13	188

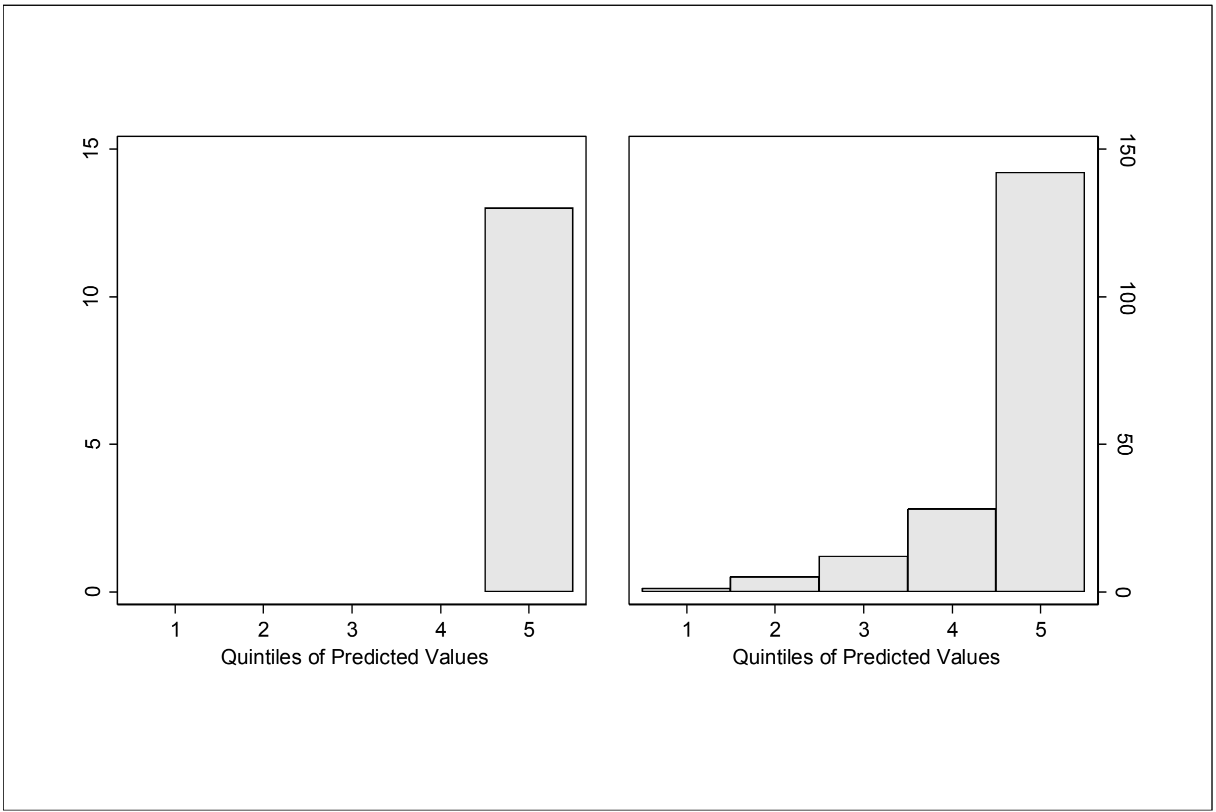

Figure 5.
Out-of-Sample Predictions: Forecasting

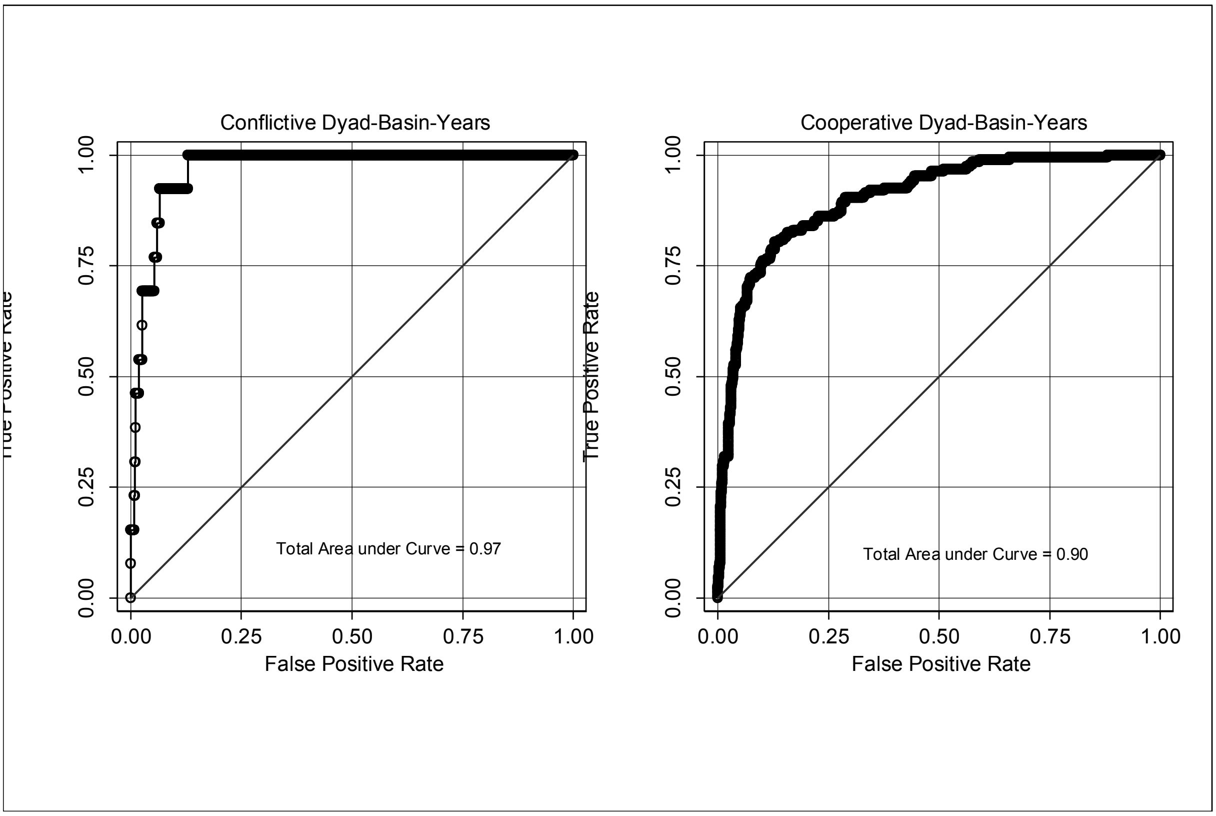

Figure 6.
Out-of-Sample Predictions: Forecasting via ROC Plots

Table 6
Basins at Risk and Cooperative Basins in Comparison

Basins at Risk – Yoffe et al. (2003)	*Basins at Risk – This Paper*	*Cooperative Basins – This Paper*
Aral Sea	Asi/Orontes	Buzi
Asi/Orontes	Atrak	Danube
Ca	Baraka	Fenney
Chiloango	Daoura	Hari/Harirud
Cross	Buzi	Incomati
Drin	Colorado	Indus
Ganges-Brahmaputra-Meghna	Cross	Jordan
Han	Dasht	Mekong
Indus	Dnieper	Niger
Irrawaddy	Dniester	Nile
Jordan	Don	Senegal
Kune	Dra	
Kura-Araks	Elancik	
La Plata	Fenney	
Lake Chad	Firth	
Lempa	Gash	
Limpopo	Grijalva	
Mekong	Guir	
Nile	Han	
Ob	Hari/Harirud	
Okavango	Ili/Kunes He	
Red	Indus	
Saigon	Kaladan	
Salween	Kogilnik	
Senegal	Lake Natron	
Song Vam Co Dong	Lake Turkana	
Tigris-Euphrates	Medjerda	
Yalu	Mius	
Zambezi	Ob	
	Oued Bon Naima	
	Ouémé	
	Rio Grande (North America)	
	Sabi	
	Samur	
	Sarata	
	St. John (North America)	
	Sujfun	
	Tafna	
	Tigris-Euphrates	
	Tijauana	
	Tumen	
	Umba	
	Volga	
	Yakui	

References

Bechtel, Michael, and Dirk Leuffen. 2010. Forecasting European Union Politics: Real-Time Forecasts in Political Science Time Series Analysis. *European Union Politics* 11 (2): 309-327.

Beck, Nathaniel, Jonathan Katz, and Richard Tucker. 1998. Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable. *American Journal of Political Science* 42 (4): 1260-1288.

Bernauer, Thomas, and Anna Kalbhenn. 2010. The Politics of International Freshwater Resources. In *The International Studies Encyclopedia*, edited by Robert Denemark, 5800-5821. Hoboken, NJ: Wiley-Blackwell.

Brochmann, Marit. 2012. Signing River Treaties – Does It Improve River Cooperation? *International Interactions* 38 (2): 141-163.

Brochmann, Marit, and Nils Petter Gleditsch. 2012. Shared Rivers and Conflict - A Reconsideration. *Political Geography* 31 (8): 519-527.

Brochmann, Marit, and Paul Hensel. 2009. Peaceful Management of International River Claims. *International Negotiation* 14 (2): 393-418.

De Stefano, Lucia, Paris Edwards, Lynette de Silva, and Aaron Wolf. 2010. Tracking Cooperation and Conflict in International Basins: Historic and Recent Trends. *Water Policy* 12 (6): 871-884.

Dinar, Ariel, Brian Blankespoor, Shlomi Dinar, and Pradeep Kurukulasuriya. 2010. The Impact of Water Supply Variability on Treaty Cooperation between International Bilateral River Basin Riparian States. *World Bank Policy Research Working Paper Series No. 5307*.

Dinar, Ariel, and Shlomi Dinar. 2003. Recent Developments in the Literature on Conflict and Cooperation in International Shared Water. *Natural Resources Journal* 43 (4): 1217-1287.

Espey, Molly, and Basman Towfique. 2004. International Bilateral Water Treaty Formation. *Water Resources Research* 40 (5): W05S05 (1-8).

Furlong, Kathryn, Nils Petter Gleditsch, and Håvard Hegre. 2006. Geographic Opportunity and Neomalthusian Willingness: Boundaries, Shared Rivers, and Conflict. *International Interactions* 32 (1): 79-108.

Gerlak, Andrea, Keith Grant. 2009. The Correlates of Cooperative Institutions for International Rivers. In *Mapping the New World Order*, edited by Thomas Volgy, Zlatko Šabič, Petra Roter, and Andrea Gerlak, 114-147. Hoboken, NJ: Wiley-Blackwell.

Gleditsch, Kristian Skrede, and Michael Ward. 2013. Forecasting is Difficult, Especially the Future: Using Contentious Issues to Forecast Interstate Disputes. *Journal of Peace Research* 50 (1): 17-31.

Gleditsch, Nils Petter, Kathryn Furlong, Håvard Hegre, Bethany Lacina, and Taylor Owen. 2006. Conflicts Over Shared Rivers: Resource Scarcity or Fuzzy Boundaries? *Political Geography* 25 (4): 361-382.

Hensel, Paul, Sara McLaughlin Mitchell, Thomas Sowers, and Clayton Thyne. 2008. Bones of Contention: Comparing Territorial, Maritime, and River Issues. *Journal of Conflict Resolution* 52 (1): 117-143.

Kalbhenn, Anna, 2011. Liberal Peace and Shared Resources - A Fair-Weather Phenomenon? *Journal of Peace Research* 48 (6): 715-735.

Kalbhenn, Anna, and Thomas Bernauer. 2012. *International Water Cooperation and Conflict: A New Event Dataset*. ETH Zurich. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2176609 and at http://www.ib.ethz.ch/research/data, accessed October 21, 2013.

Marshall, Monty, and Keith Jaggers. 2004. *POLITY IV Project: Political Regime Characteristics and Transitions*. *User's Manual*. College Park, MD: University of Maryland.

Owen, Taylor, Kathryn Furlong, and Nils Petter Gleditsch. 2004. *Codebook for the Shared River Basin and GIS Database*. Oslo: Peace Research Institute.

Stinnett, Doug, and Jaroslav Tir. 2009. The Institutionalization of River Treaties. *International Negotiation* 14 (2): 229-251.

Tir, Jaroslav, and Ackerman, J., 2009. Politics of Formalized River Cooperation. *Journal of Peace Research* 46 (5): 623-640.

Toset, Hans Petter Wollebæk, Nils Petter Gleditsch, and Håvard Hegre. 2000. Shared Rivers and Interstate Conflict. *Political Geography* 19 (8): 971-996.

Ward, Michael, Brian Greenhill, and Kristin Bakke. 2010. The Perils of Policy by P-Value: Predicting Civil Conflicts. *Journal of Peace Research* 47 (4): 363-375.

Wolf, Aaron, Jeffrey Natharius, Jeffrey Danielson, Brian Ward, and Jan Pender. 1999. International River Basins of the World. *Water Resources Development* 15 (4): 387-427.

Wolf, Aaron, Kerstin Stahl, and Marcia Macomber. 2003a. Conflict and Cooperation within International River Basins: The Importance of Institutional Capacity. *Water Resources Update* 125 (2): 31-40.

Wolf, Aaron, Shira Yoffe, and Mark Giordano. 2003b. International Waters: Identifying Basins at Risk. *Water Policy* 5 (1): 29-60.

Yoffe, Shira, Aaron Wolf, and Mark Giordano. 2003. Conflict and Cooperation over International Freshwater Resources: Indicators of Basins at Risk. *Journal of the American Water Resources Association* 39 (5): 1109-1125.

Yoffe, Shira, Greg Fiske, Mark Giordano, Kelli Larson, Kerstin Stahl, and Aaron Wolf. 2004. Geography of International Water Conflict and Cooperation: Data Sets and Applications. *Water Resources Research* 40 (5): 1-12.

Zawahri, Neda, and Andrea Gerlak. 2009. Navigating International River Disputes to Avert Conflict. *International Negotiation* 14 (2): 211-227.

Zawahri, Neda, and Sara McLaughlin Mitchell. 2011. Fragmented Governance of International Rivers: Negotiating Bilateral vs. Multilateral Treaties. *International Studies Quarterly* 55 (3): 835-858.

Zeitoun, Mark, and Naho Mirumachi. 2008. Transboundary Water Interaction I: Reconsidering Conflict and Cooperation. *International Environmental Agreements* 8 (4): 297-316.

Zeitoun, Mark, Naho Mirumachi, and Jeroen Warner. 2010. Transboundary Water Interaction II: Soft Power Underlying Conflict and Cooperation. *International Environmental Agreements* 11 (2): 159-178.

Appendix – Table

Determinants of International River Conflict and Cooperation – Overview of Variables in Data

Variable	*Theoretical Rationale*	*Conceptual Description*	*Source*
Territory in Basin	The larger the percentage of a basin residing in a state, the less dependent it is on other states, making conflict less likely (e.g., Brochmann and Gleditsch 2012; Zawahri and Mitchell 2011)	Share of a country's surface area located in a given international river basin; weakest-link specification with the lowest value in a dyad determining the value of the final item	Wolf et al. 1999
External Water Dependence	The higher the external dependence on freshwater, the more salient the issue, and the more likely it is that conflict emerges (e.g., Zawahri and Mitchell 2011)	Extent to which a country is dependent on external sources of freshwater; weakest-link specification with the lowest value in a dyad determining the value of the final item	AQUASTAT Database
Precipitation	The higher the precipitation, the less salient is the issue of freshwater; this decreases the risk of conflict (e.g., Zawahri and Mitchell 2011)	Average water precipitation in depth (mm/year); weakest-link specification with the lowest value in a dyad determining the value of the final item	AQUASTAT Database
GDP per capita, Large (log)	The wealthier two states, the higher the likelihood of cooperation (Brochmann 2012, 153); wealth is also an important aspect of the gravity model (Brochmann and Gleditsch 2012)	Natural log of GDP per capita in constant 2000 USD in the largest economy of both states in a dyad	Gleditsch 2002
GDP per capita, Small (log)	The wealthier two states, the higher the likelihood of cooperation (Brochmann 2012, 153); wealth is also an important aspect of the gravity model (Brochmann and Gleditsch 2012)	Natural log of GDP per capita in constant 2000 USD in the smallest economy of both states in a dyad	Gleditsch 2002
Population, Large (log)	Populous states have a higher risk of conflict (Brochmann and Gleditsch 2012, 523)	Natural log of the population in the largest country of both states in a dyad	Gleditsch 2002
Population, Small (log)	Populous states have a higher risk of conflict (Brochmann and Gleditsch 2012, 523)	Natural log of the population in the smallest country of both states in a dyad	Gleditsch 2002
Democracy	Liberal arguments postulate that joint democracies are more likely to cooperate with each other	Polity2 item of the Polity IV Data with a weakest-link specification with the lowest value in a dyad determining the value of the final item	Marshall and Jaggers 2004
Alliance	Alliances constitute another form of cooperation; if two states are part of an alliance, they might cooperate in other issue areas as well (Brochmann 2012,	Dichotomous variable that receives a value of 1 if two countries in a dyad are part of an entente or a defense pact	Gibler and Sarkees 2004

Variable	Theoretical Rationale	Conceptual Description	Source
	152)		
IGO Membership	The joint membership in international organizations leads to frequent encounters and interactions between states; in turn, this lowers uncertainty and facilitates trust, leading to more cooperation (Kalbhenn 2011)	The number of joint memberships in international organizations	Pevehouse et al. 2004
Legal System Similarity	The more similar the legal system of two states, the lower the transaction costs and uncertainty about an issue; this should enhance cooperation (e.g., Zawahri and Mitchell 2011).	Categories used are civil law, common law, Islamic law, and mixed law; when two states in a dyad share the same legal tradition, this item is coded as 1 (0 otherwise)	Zawahri and Mitchell 2011
Distance (log)	The higher the distance, the less likely that conflict emerges (e.g., Brochmann and Gleditsch 2012)	Natural logarithm of the distance between the capital cities of the two states in a dyad	Gleditsch and Ward 1999
Contiguity	If two countries share a land boundary, the more likely that conflict emerges (e.g., Brochmann and Gleditsch 2012)	Dichotomous variable receiving the value of 1 if two states in a dyad share a land boundary (0 otherwise)	UCDP 2008
Number of Riparian States	Basin-specific effects: the more riparian states do exist, the more difficult it may be to agree on common cooperative efforts (Kalbhenn 2011)	Count variable for the number of states in a basin	Kalbhenn and Bernauer 2012
Upstream Power	Geographical configuration and power aspects: upstream states are generally more powerful, while this can be furthered by more military capabilities (e.g., Brochmann and Gleditsch 2012; Zawahri and Mitchell 2011)	Correlates of War National Material Capabilities Data for the upstream state	Singer et al. 1972
Downstream Power	Geographical configuration and power aspects: downstream states are generally less powerful, while this can be outweighed by more military capabilities (e.g., Brochmann and Gleditsch 2012; Zawahri and Mitchell 2011)	Correlates of War National Material Capabilities Data for the downstream state	Singer et al. 1972

References of the Appendix

Brochmann, Marit. 2012. Signing River Treaties - Does It Improve River Cooperation? *International Interactions* 38 (2): 141-163.

Brochmann, Marit, and Nils Petter Gleditsch. 2012. Shared Rivers and Conflict - A Reconsideration. *Political Geography* 31 (8): 519-527.

Gleditsch, Kristian Skrede. 2002. Expanded Trade and GDP Data. *Journal of Conflict Resolution* 46 (5): 712-724.

Gleditsch, Kristian Skrede, and Michael Ward. 1999. A Revised List of Independent States since 1816. *International Interactions* 25 (4): 393-413.

Gibler, Douglas, and Meredith Sarkees. 2004. Measuring Alliances: The Correlates of War Formal Interstate Alliance Data Set, 1816-2000. *Journal of Peace Research* 41 (2): 211-222.

Kalbhenn, Anna, 2011. Liberal Peace and Shared Resources - A Fair-Weather Phenomenon? *Journal of Peace Research* 48 (6): 715-735.

Kalbhenn, Anna, and Thomas Bernauer. 2012. *International Water Cooperation and Conflict: A New Event Dataset*. ETH Zurich. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2176609 and at http://www.ib.ethz.ch/research/data, accessed October 21, 2013.

Marshall, Monty, and Keith Jaggers. 2004. *POLITY IV Project: Political Regime Characteristics and Transitions*. *Dataset User's Manual*. College Park, MD: University of Maryland.

Pevehouse, Jon, Timothy Nordstrom, and Kevin Warnke. 2004. The Correlates of War 2 International Governmental Organizations Data Version 2.0. *Conflict Management and Peace Science* 21 (2): 101-119.

Singer, David, *Stuart* Bremer, and John Stuckey. *1972.* Capability Distribution, Uncertainty, and Major Power War, 1820-1965. In *Peace, War, and Numbers*, edited by Bruce Russett, 19-48. Beverly Hills, CA: SAGE.

Uppsala Conflict Data Program (UCDP). 2008. *UCDP Database*. Department of Peace and Conflict Research. Uppsala: Uppsala University.

Wolf, Aaron, Jeffrey Natharius, Jeffrey Danielson, Brian Ward, and Jan Pender. 1999. International River Basins of the World. *Water Resources Development* 15 (4): 387-427.

Zawahri, Neda, and Sara McLaughlin Mitchell. 2011. Fragmented Governance of International Rivers: Negotiating Bilateral vs. Multilateral Treaties. *International Studies Quarterly* 55 (3): 835-858.