Location, Location, Location: An MCMC Approach to Modeling the Spatial Context of War and Peace

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This article demonstrates how spatially dependent data with a categorical response variable can be addressed in a statistical model. We introduce the idea of an autologistic model where the response for one observation is dependent on the value of the response among adjacent observations. The autologistic model has likelihood function that is mathematically intractable, since the observations are conditionally dependent upon one another. We review alternative techniques for estimating this model, with special emphasis on recent advances using Markov chain Monte Carlo (MCMC) techniques. We evaluate a highly simplified autologistic model of conflict where the likelihood of war involvement for each nation is conditional on the war involvement of proximate states. We estimate this autologistic model for a single year (1988) via maximum pseudolikelihood and MCMC maximum likelihood methods. Our results indicate that the autologistic model fits the data much

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better than an unconditional model and that the MCMC estimates generally dominate the pseudolikelihood estimates. The autologistic model generates predicted probabilities greater than 0.5 and has relatively good predictive abilities in an out-of-sample forecast for the subsequent decade (1989 to 1998), correctly identifying not only ongoing conflicts, but also new ones.

1 Introduction

Many theories of world politics recognize the *interdependence* among actors and events. Indeed, international relations is typically defined as the study of relations among states, which are considered the main actors in world politics. This means that actors as well as actions are strategically interdependent, a point creatively and forcefully made by Signorino (1999). Despite this emphasis on *relations among countries* in theories of international relations, most empirical models of war and peace examine linkages from a single state's attributes to its behavior, largely ignoring the independence among actors.[1] Ignoring the interdependence among observations is a serious problem in world politics scholarship, and it plagues our attempts to find better empirical models on which to base forecasts.

In this article, we focus on a particular form of dependence between states, namely, how space or regional context conditions the prospects for war and peace. The basic insight we propose herein is that a state's probability of conflict involvement is highly dependent upon the distribution of conflict and peace in other states. Regional connections among countries, such as alliances and the extent of conflict prevailing in a region, condition the behavior of states in the conflicting as well as the peaceful domains of world politics. We base this belief on our studies illustrating the power of regional context in empirical models of war (Gleditsch and Ward 2000; Gleditsch 2002). One important implication of this claim is that observations are *not* exchangeable. Curiously, such interdependence is typically lacking in empirical models of international relations and world politics. Although neglect of the regional context of war and peace certainly is not the only problem in existing empirical work, we surmise that this lack of realism constitutes a particularly severe source of bias against accurate forecasting.

We test our claim about the importance of regional context by first estimating an extremely simple model of conflict, based on conditional assessments of the conflict involvement of all other countries, the distance among states, and their regime characteristics in 1988. Our specific approach is an autologistic model—explained more formally in Section 3—estimated via maximum pseudolikelihood (MPL) and Markov Chain Monte Carlo (MCMC) maximum likelihood approximations. We demonstrate that a conditional model of conflict is superior to a standard logistic model of conflict treating the observations as independent. We use these results—based on the analysis of a single year, 1988—to forecast participation in conflict over the next decade, 1989–1998. This test demonstrates the power of incorporating dependence across space in world politics: Even over the sea of change in the post-Cold War area, our simple model, based exclusively on a single covariate and local dependence, accurately identifies about half of the international and civil wars participants between 1989 and 1998.

[1] Schrodt and Mintz (1988) is an exception to this. This article used a conditional probability model to predict the probability of hostile and cooperative interaction in one dyad given interactions in other dyads. Unfortunately this work has been widely ignored.

2 Geography, Conflict, and Peace

The importance of geography in shaping the opportunity and willingness to engage in cooperation and conflict is widely recognized (Most and Starr 1989). Numerous studies have shown that, once under way, wars have a tendency to diffuse to neighboring states. Many studies routinely introduce distance between states as a "control variable" for the opportunity to engage in war. However, only quite recently have scholars begun to explore international conflict and cooperation from a perspective that incorporates regional context in a systematic fashion. In this section, we briefly review existing applications of insights from spatial statistics to the study of international relations.

Graph theory shows how relations among units can be represented in a matrix format (Harary et al. 1965). In the field of *spatial statistics*, the structure of dependence or influences among units are typically modeled through a matrix specification of dependence based on the geographical distance among units, where the entries $w_{i,j}$ of an $n \times n$ connectivity matrix $\mathbf{W}$ acquire nonzero entries if units i and j are connected or geographical "neighbors." In the social sciences, statistical investigations based on such techniques were popularized through the so-called *spatial econometric* approach surveyed by Anselin (1988). Anselin emphasizes two sets of models of spatially correlated data. The first uses a geographically based connectivity matrix to specify a spatial autoregressive model (SAR) that introduces a spatial lag of the dependent variable. The second specifies a spatially correlated error structure (SER).

Such approaches have been used in several studies in international relations to examine the role of regional context and diffusion for phenomena including international conflict and cooperation (Gleditsch and Ward 2000), defense spending (Shin and Ward 1999), the spread of political structures and processes (O'Loughlin et al. 1998), spillover effects in economic growth (Easterly and Levine 1999), economic convergence (Lopez-Vazo et al. 1999), and the study of public goods and externalities (Murdoch et al. 1997). Useful as these studies have been, the standard framework presumes that the dependent variable is continuous. Conflict, however, is commonly thought of as a discrete event and generally measured categorically—typically as a binary variable. For a binary phenomenon such as conflict, the spatial dependence between observations is more naturally considered through a conditional probability model where the presence of conflict in neighboring countries conditions the likelihood that a state will become involved in war.

Work on international conflict—and social science more generally—has not taken advantage of the breakthroughs that have occurred in the past three decades on such conditional models for categorical variables in the statistical analysis of spatial patterns (i.e., the line of research beginning with Besag 1972, 1974). The so-called autologistic model is widely known in statistics and has been frequently used for applications in ecology and natural science but appears to have been completely ignored in the social sciences. As yet, there are no published studies in political science that incorporate the most recent modeling and statistical frameworks developed in applied statistics for modeling spatial processes.

We undertake a simple, but difficult, test to support these claims about the importance of regional context. We first estimate an overly simple model of international war, based on conditional assessments of the war behaviors of all other countries and on the regime characteristics of these states. We choose 1988 as a baseline year, the last year before the cascade of democratic change that swept across the world in the early 1990s. Then, using this baseline model—without updating the covariates—we forecast the existence of conflict over the next decade, up until 1998. This test demonstrates the power of models of international relations that do not assume complete independence of observational information about world politics since we are able to predict accurately about half of the international and civil wars that occurred in the decade between 1989 and 1998 considering the conditional dependence of conflict and a single covariate, political democracy. Our specific approach is based on an autologistic specification of the model which is then estimated *via* pseudolikelihood and MCMC maximum likelihood approximations. We demonstrate that either of these approaches is vastly superior to a simple unconditional logit model and that the MCMC maximum likelihood estimates dominate the pseudolikelihood estimates.

The unit specific covariates in our model are based on the recent research on what has become known as the *democratic peace*. The seeming absence of war among democracies was first noted by Babst (1964), but the notion that political regime structures affect the likelihood of conflict entered the mainstream of empirical research on international conflict through a series of articles by Rummel (1983, 1984, 1985) and the controversies it generated. We have previously examined the impact of regime structures and changes in these on conflict in a series of papers (Ward and Gleditsch 1998; Gleditsch and Ward 2000). Ward and Gleditsch (1998) essentially ignored any dependence among the observations over time and across space; in Gleditsch and Ward (2000) we examined the dependence of peace and war over time and also sought to take explicitly into account dependence across units in space by a model specifying the likelihood of war as conditional on neighboring entities (see also Gleditsch 2002). This prior work demonstrated that both conflict and democracy are clustered in space and that ignoring this correlation can yield incomplete and misleading results. In the next section we build on this insight and focus on a model emphasizing two basic hypotheses concerning international conflict: the negative impact of high levels of democracy on conflict propensity and the contagion effects of conflicts in surrounding regions.

3 An Autologistic Model of Democracy and War

Our basic model is an autologistic model of the likelihood that a state i will be involved in a conflict at time t. We assume that the regional dependence in the distribution of conflict takes the form of a local Markov random field. A Markov field can be seen as a spatial analogy to the more familiar first-order Markov property in time. For the set of N spatial units, $Pr(x_i \mid x_j, j \neq i)$ depends only on x_j if and only if j is a neighbor of i (Ripley 1988). The neighborhood structure can be specified by a graph, as discussed above.

Operationally, we specify the dependencies among the N countries by a binary $n \times n$ distance-based connectivity matrix, where entries $w_{i,j}$ acquire a value of 1 if states i and j are considered adjacent or "close." We generate the $\mathbf{W}$ matrix from a new data set on the minimum distances between polities in the international system (Gleditsch and Ward 2001). For this study, we chose a distance of 475 km or less to indicate adjacency.[2]

Two covariates capture the level of democracy and the regional context of democracy: $d_{i,t}$ represents the level of democracy at time t in country i for all countries $(1, \ldots, n)$ and $d'_{i,t}\mathbf{W}^s$ captures the average level of democracy in proximate countries, with $\mathbf{W}^s$ denoting a connectivity matrix $\mathbf{W}$ that has been row standardized. The democracy scores are taken from the Polity 98 data.

Adding an intercept, α, and a spatial covariate, $y'_i\mathbf{W}$, to the other terms yields

$$\alpha + \beta_1 d_i + \beta_2 d'_i \mathbf{W}^s + \gamma y'_i \mathbf{W},$$

[2]This is an arbitrary choice between direct contiguity or land borders and the largest distance available in the database, 950 km. A wide variety of criteria can be examined with our data, however.

where $y_i'\mathbf{W}$ is the sum of neighbors in conflict for a given definition of neighbors contained in the connectivity matrix, $\mathbf{W}$. More generally, we define η_i as a $k \times i$ matrix of k exogenous variables $\mathbf{X}_i$, the neighborhood sum, $y_i'\mathbf{W}$, defined as $\widetilde{y}_i$, and the associated vector β_k of parameters:

$$\eta_i = \alpha + \mathbf{X}_i'\beta_k + \gamma\widetilde{y}_i.$$

This permits a simple statement of the autologistic:

$$Pr[y_i = 1 \mid \widetilde{y}_i] = \frac{e^{\eta_i}}{1 + e^{\eta_i}};$$
$$Pr[y_i = 1 \mid \widetilde{y}_i] = \frac{e^{\alpha+\beta_1 d_i+\beta_2 d_i'\mathbf{W}^s+\gamma y_i'\mathbf{W}}}{1 + e^{\alpha+\beta_1 d_i+\beta_2 d_i'\mathbf{W}^s+\gamma y_i'\mathbf{W}}}.$$

If $\gamma = 0$, this is a standard logistic model where the observations are independent of one another. In a "pure" autologistic model where all β_k are 0, the unit specific covariates exert no independent influence on the dependent variable once the conditional dependence among the observations is taken into account.[3]

We examine this simple model using data on political authority structures from the 21-point institutionalized democracy scale in Polity 98, ranging from -10 for highly autocratic to $+10$ for highly democratic countries. Our conflict variable is a binary indicator of whether states participate in wars, either international or civil, involving more than 1000 battle deaths. This is based on data from the Correlates of War project's International and Civil War data (Singer and Small 1994), updated beyond 1992 with the major wars in the conflict data compiled at the Department of Peace and Conflict Research at Uppsala University (Wallensteen and Sollenberg 1999).[4] To ignore the added complications from dependence of peace and war over time we estimate our model on data for a single time period only.[5] We first examine this model for 1988 data. We then use these estimates to forecast conflict over the subsequent 10-year period.

Our model is exceedingly parsimonious (i.e., simplistic), with only two covariates: the level of democracy in a country and the average level of democracy in the surrounding countries. This quite simple model, however, will enable us to see how much information exists in the spatial distribution of conflict itself and further enable us to examine its diffusion. In addition, prediction from estimates based on the 1988 data for the subsequent decade should represent a hard case for the autologistic process: 1988 was the last year before the

[3] A different version of this model could examine the lagged propensities instead of the lagged realized conflict. We have used the latter, keeping with the general tradition in environmental and biological studies that have developed and employed the autologistic approach.

[4] We do not attempt to distinguish between interstate wars—where the opposing parties are both nation states—and "other wars"—where nation states engage in conflict with nonstate entities. Although the Correlates of War project classifies conflicts as interstate, extrastate, and civil wars, the distinction is often difficult to make in practice. The Russian engagement in the Afghan war, for example, is classified as international participation in a civil war. While space precludes a full discussion of these issues here, many post-Soviet conflicts such as Nagorno-Karabakh and Chechnya illustrate the difficulties in separating "international" and "civil" wars. Whereas many models of international conflict use *dyads* or pairs of states as the unit of analysis, our interest here is not limited to conflicts where both the antagonists are nation states. The democratic peace is usually thought of as a proposition about relations between nation states. Hegre et al. (2001) find that democracy also reduces the risk of civil war within states.

[5] Our empirical model covers a single cross section only and does not address the temporal dynamics. As such, our lagged spatial realized covariates may reflect over-time dynamics.

fall of the Berlin wall, and many changes were afoot around the globe. The forecast beyond 1988 into the next decade after the Cold War constitutes a challenging test of whether this simple autologistic model picks up on consistent structure in the relationship among geography, democracy, and conflict.

4 Estimation Methods

The autologistic model has a likelihood function that is mathematically intractable since the observations y_i are conditionally dependent upon each other (Besag 1974). Three computational methods for the autologistic model have been proposed to solve this problem. Besag (1974) devised a coding method that reduced the dependencies to a few adjacencies, assuming that all other observations are independent and exchangeable. This allows maximum likelihood estimation but is wrought with other problems. This method is inefficient, and the many possible coding schemes can give inconsistent results (e.g., Huffer and Wu 1998). This technique is little used in practice.

Besag (1975) developed a MPL method that largely replaced the original coding method (see also Ripley 1988; Strauss and Ikeda 1990). The MPL approach is closely related to the coding method and can be thought of as a weighted average of different coding methods. This method is easy to implement, is more efficient than the original coding method, and has been shown to have reasonable asymptotic properties. The major disadvantage of the pseudolikelihood approach is that it tends to be inefficient, *especially* when spatial interaction is strong (Besag and Moran 1975; Besag 1977; Huffer and Wu 1998).

More recently, it has become possible to use simulation approaches—namely, the MCMC method—to get approximations that are closer to the full likelihood function. These methods are computationally intensive but allow one to approximate maximum likelihood estimates for any family of distributions with probability densities known up to a constant of proportionality.[6]

One basic approach detailed by Geyer and Thompson (1992) is quite simple in conception. A probabilistic random map generated from the autologistic model can be defined by the parameters $\theta = (\alpha, \beta_k, \gamma)$ and the sufficient statistics,[7] $s(y)$, given by

$$s(y) = \left(\sum_{i=1}^{n} y_i, \sum_{i=1}^{n} X_i y_i, \frac{1}{2} \sum_{i=1}^{n} \widetilde{y_i} \right).$$

For any vector of parameters ψ corresponding to θ, simulated values for y_i can be obtained. Pseudolikelihood estimates of parameters are frequently used for initial values of ψ. A Gibbs sampler (Geman and Geman 1984) is used to generate a set of samples, conditioned on the parameters ψ. Sufficient statistics are calculated, and from these sufficient statistics, it is also possible to approximate the likelihood function for θ. The MCMC maximum likelihood, found through these approximations, is obtained by solving the score equation, typically by Newton–Raphson methods:

$$\frac{\sum_{j=1}^{m} s(y_m) e^{(\hat{\theta}-\psi)' s(y_m)}}{\sum_{j=1}^{m} e^{(\hat{\theta}-\psi)' s(y_m)}} = s(y),$$

[6]Gelman et al. (1995) and Jackman (2000) provide overviews of MCMC estimation in the context of Bayesian statistics.

[7]A sufficient statistic $T(X)$ for y contains all the information about y that is available in the observed data X.

Table 1 Logistic, autologistic MCMC maximum likelihood, and pseudolikelihood parameter estimates for 1988 data for 139 countries

			Spatial parameter	
	Intercept (α)	*Democracy* (β_1)	*Democracy* (β_2)	*Conflict* (γ)
Pseudolikelihood $\hat{\psi}$	**−1.840**	−0.020	0.013	**0.298**
MCMC maximum likelihood $\hat{\theta}$	**−1.712**	**−0.053**	−0.003	**0.261**
Logistic	**−1.309**	−0.022	−0.015	—
Pseudolikelihood SE	0.333	0.033	0.051	0.126
MCMC SE	0.060	0.006	0.010	0.013
Logistic SE	0.218	0.033	0.048	—

Note. The effect of neighborhood conflict is shown to be strong.

where m is the number of sampled simulated maps and $s()$ is the vector of sufficient statistics.[8] Geyer and Thompson (1992) show that this approach recovers the maximum likelihood parameter estimates. Updating strategies can follow a variety of MCMC strategies. We have used Gibbs sampling and have updated all the parameters as a bloc, since our model has so few parameters. If more covariates were involved it could be desirable to update parameter by parameter, iterating over different order for the parameters as well as for the starting point within the space, i.e., the country.

The MCMC approach to the autologistic model has been used for parameter estimation of spatially correlated data (Gotway and Stroup 1997; Gumpertz et al. 1997, 1999) as well as for image recognition/reconstruction for incomplete spatial data (Hoeting et al. 2000). Since the units in our analysis are geographical areas or irregular lattices that may or may not be connected to other units rather than point observations on a map, the structure of our data looks somewhat different from that of many of these applications. The structure of our problem, however, is conceptually equivalent.

5 Empirical Results

The empirical results of our model for the 1988 data are presented in Table 1. The first row in the upper part of the table displays the pseudolikelihood (MPL) estimates $\hat{\psi}$ of the autologistic model. The MCMC estimates of the parameters of the autologistic model are displayed in the second row. We generated our Monte Carlo sample by 1000 iterations of the Gibbs sampler, using ψ as starting values and a burn-in period of 100 samples, gathering the sufficient statistics at every second iteration. Finally, the third row in the upper part of Table 1 displays the estimates from a standard logistic model treating the observations y_i as independent of one another.[9] The standard error estimates for the three estimation methods are displayed in the lower part of the table.

[8]Newton–Raphson methods are a crude, iterative way to minimize a function with respect to the set of parameters θ. The basic iteration is given by $\theta_{i+1} = \theta - \mathbf{G}^{-1}(\theta_i)g(\theta_i)$, with $g(\theta_i)$ a vector of derivatives of f with respect to the θ_i and $\mathbf{G}(\theta_i)$ is the $m \times m$ matrix of second derivatives of f. This method is very fast if it begins close to the minimum but slow and stubborn if it does not: **G** may become negative definite in such cases. Newton–Raphson algorithms can also produce exploding parameter vectors as well as cyclical results.

[9]Including regional dummy variables is sometimes suggested as a simple alternative to remedy problems of regional differences and heterogeneity among observations. Allowing different constant terms for regions, however, simply treats such differences as given and essentially ignores conditional dependence. We question the usefulness of this approach but also estimate an unconditional logit with regional dummy variables for comparison. In this case, none of the regional dummy variables are significant. Nor does this model predict the presence of a single conflict.

In general, the MCMC estimates ($\hat{\theta}$) and the pseudolikelihood estimates ($\hat{\psi}$) of the parameters are quite similar, but the standard errors of the MCMC estimates are considerably smaller. As can be seen from the high positive estimates of the neighboring conflict parameter $\hat{\gamma}$, both the pseudolikelihood parameter estimates and the MCMC estimates yield strong evidence that countries that are surrounded by conflictual countries have a much higher likelihood of participating in a conflict, either civil or international.

As would be expected from the idea that greater levels of democracy constrain the likelihood of war involvement, all three estimators indicate that a high level of democracy has a negative effect on the probability of conflict. However, only the MCMC estimates suggest any substantial damping effect of the level of democracy on the probability of conflict. The standard errors are also large relative to the coefficient estimates for both the pseudolikelihood autologistic estimates and the nonconditional logit estimates. In sum, even though the democracy parameter would not be significantly different from zero based on the MPL or logit estimates, all other things being set aside as equal, the MCMC estimates of the autologistic model suggest that democracy exerts a robust negative influence on the likelihood that a country will be involved in a domestic or international conflict of substantial magnitude. The estimate for the spatial context of democracy is close to zero, with a fairly large standard error; by traditional standards this would not be a powerful covariate.

It has been noted that many models of international conflict generate rather low predicted probabilities. Beck et al. (2000) have argued that virtually no *dyadic* studies of international conflict (excluding those sampling on the dependent variable) can successfully "postdict" conflict in the observed data with a predicted probability greater than the typical threshold used in many fields, $\hat{\pi} > 0.5$. Similarly, studies of civil wars within states typically have a poor predictive ability. Studies claiming to be able successfully to "postdict" internal conflict have, furthermore, often suffered from failing to take into account sampling issues (King and Zeng 2001) or merely argued that countries with the "highest" residuals are those most prone to conflict (e.g., Gurr and Moore 1997).

Similarly, the unconditional logit model and the pseudolikelihood estimates of the autologistic model in Table 1 do not yield predicted probabilities above 0.5 for any of the observations. However, the predicted probabilities from the MCMC estimates of the autologistic model do in fact exceed this threshold (see Table 2) in 7 of the 139 cases in the 1988 data, admittedly a small proportion but certainly not an empty set. Figure 1 presents the probability density for the estimates from the autologistic model. Moreover, two of the seven countries predicted to be at war actually were: Iraq and Syria were both involved in conflicts in 1988.

Such a comparison leaves unincorporated conditional information—including both errors and covariance—that might be introduced by the model itself and is, therefore, not an adequate reflection of the model's predictive power. For a more realistic assessment we

Table 2 Actual and predicted conflicts for 1988 using $\hat{\theta}$ estimates for the autologistic model

	Observed	
Predicted	*No*	*Yes*
No	103	29
Yes	5	2

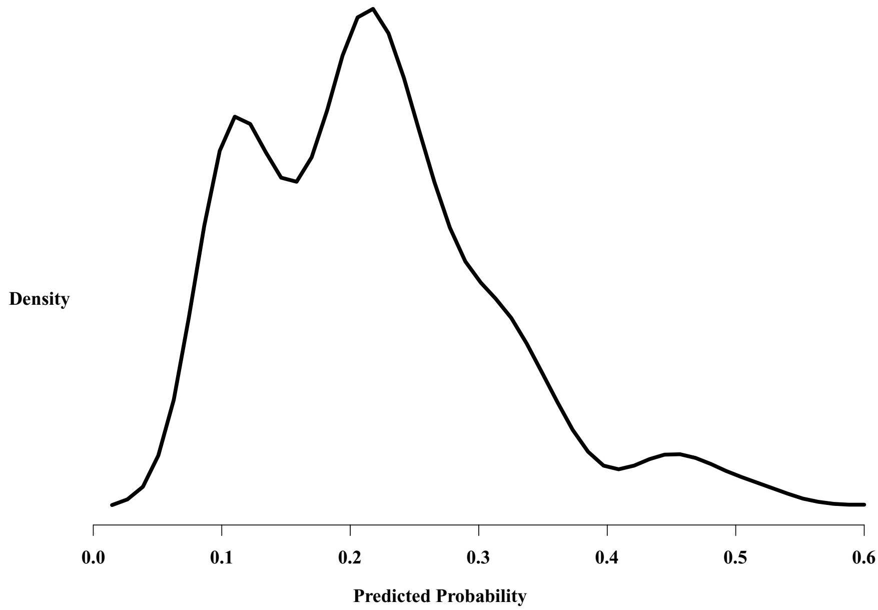


Fig. 1 Density function for predicted probability of conflict. The density plot of predicted probabilities illustrates that there are at least two, and probably three, basic groups of predictions, including those in the small cluster above about 0.4, which are taken to represent predicted conflicts.

conduct a simulation, using the estimated $\hat{\theta}$ to produce predicted probabilities of conflict where, instead of using the observed data on conflict—i.e., the data that were used in generating the estimates—we update the conflict values based on the model predictions during the simulation. Based on our inspection of Fig. 1 we use 0.35 as a cutoff value for predicting conflict.

Our simulation requires a starting value for conflict. We use the current state of conflict in 1988. We simulate conflict based on the autologistic model for 1000 iterations in which the presence of conflict is turned on or off in each country. The simulated current state of conflict is then used as input values, and the process is repeated until it settles down, usually after several iterations. Furthermore, we randomize the order in which the different locations are visited in each iteration.[10] This dynamic use of the estimated coefficients is more faithful to the autologistic formulation. Table 3 shows that, in this instance, we are able to predict 17 conflicts correctly. We miss 14 actual conflicts and have 39 false positives or predicted conflicts that do not occur.

How sensitive is the share of cases correctly predicted by the autologistic model to changes in the prediction threshold $\hat{\pi}$?[11] If we vary the relative weighting of missed

[10] As a supplement to the deterministic simulation, we also used an alternative approach where we averaged predicted values from all previous iterations over the model to determine $\tilde{y}$. The two approaches yield very similar results. We also used a much larger number of iterations, 10^3. This produced virtually identical results.

[11] The appropriate threshold of $\hat{\pi}$ above which we would consider a conflict predicted depends upon the relative costs of not predicting or missing an actual conflict (i.e., $\hat{Y} = 0 \mid Y = 1$) versus falsely predicting conflicts where these did not occur (i.e., $\hat{Y} = 1 \mid Y = 0$). If C is the ratio of how much more costly it is to miss a conflict than to falsely predict one, the optimal prediction in terms of minimizing cost is a threshold, $\hat{\pi} > 1/(1 + C)$. A $\hat{\pi} = 0.35$ implies a $C = 1.83$, or that false negatives are considered about twice as costly as false positives. King and Zeng (2001) discuss the choice of threshold in the context of forecasting state failure.

Table 3 Actual and predicted conflicts for 1988 using $\hat{\theta}$ estimates for the autologistic model via MCMC

	Observed	
Predicted	*No*	*Yes*
No	69	14
Yes	39	17

predictions relative to false positives, does the MCMC autologistic perform consistently better than the other two alternatives? King and Zeng (2001) propose using so-called *receiver-operating characteristic* (ROC) plots to evaluate model performance. The ROC plot indicates the fraction of zeros correctly predicted along the vertical axis and the fraction of ones correctly predicted along the horizontal axis for different values of the cost ratio C between missed ones and falsely predicted ones. Higher curves above the diagonal indicate better model performance.

Figure 2 displays ROC curves indicating how well the three models *predict* with the 1988 estimates. As the curves for the two versions of the autologistic are always above the standard logit, the MCMC and pseudolikelihood estimates of the autologistic model clearly dominate the unconditional logit, which is never far above the 45° line corresponding to a random guess. The choice between a standard logit model of conflict and the autologistic model that takes the conditional dependence among nations into account seems clear, irrespective of the relative weight assigned to false positives and false negatives.

The ROC approach is especially useful for comparing estimators. In our model, however, the conflict vector y in the model is not fixed but, rather, conditionally calculated at each evaluation. One changed y_i may spill over into other predicted values of different locations, i.e., y_i. The conditionality *among* y_i can lead to ROC curves that are not necessarily monotonic, as the share of correctly predicted ones conceivably could decrease with a lower prediction threshold $\hat{\pi}$. Thus, the ROC curve shown in Fig. 2 is similar to a "standard" ROC plot but differs from it in significant ways. The same information is presented in a slightly different way in Fig. 3. This graphic illustrates that for predicting both true negatives (i.e., no conflict predicted when there is none) and true positives (i.e., conflict predicted where it exists), the autologistic approach is superior to the standard logit model. At the same time it illustrates the early and complete collapse of the logit model, which begins to predict all zeros (i.e., no conflict) at $\hat{\pi}$ greater than 0.25. Optimal values for distinguishing between ones and zeros are, respectively, 0.46, 0.41, and 0.26 for the MCMC maximum likelihood, pseudolikelihood, and logit estimators. This illustrates the dominance of the autologistic estimators over the logit but also shows the slight advantage accruing to the MCMC maximum likelihood approach. The pseudolikelihood approach does do a little better at the extrema, wherein quasi-perfect predictions are obtained.

6 Out-of-Sample Prediction

The estimation results are based on a single year; accordingly, they could be erratic from one time period to another. Wars are, after all, relatively rare events. We undertake a forecasting experiment to probe whether our 1988 MCMC estimates for the autologistic indicate a genuine structure of regional dependence of conflict or merely idiosyncracies of our sample.

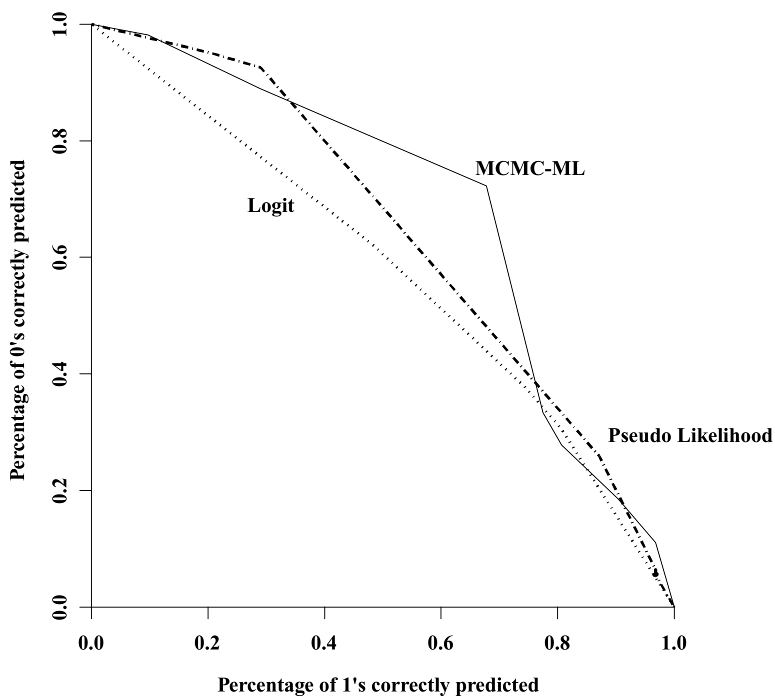
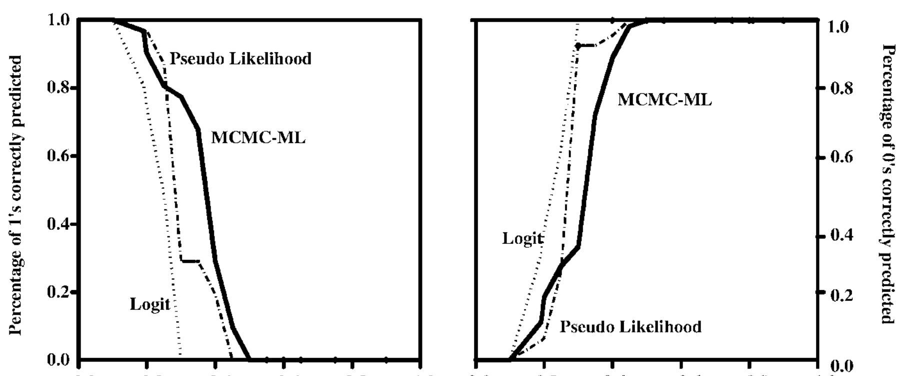


Fig. 2 ROC plot comparing the performance of the different estimators on the 1988 sample data. The standard logit model (dotted line) always underperforms the autologistic model. The solid line represents the ROC curve for the autologistic model estimated via MCMC maximum likelihood; the dashed line provides the curve for the autologistic model estimated via pseudolikelihood results; and the dotted line represents the ordinary logistic regression. The conflict vector $\tilde{y}$ is generated by averaging the predicted values from all previous iterations over the autologistic model. We ran 100 separate iterations for each value of $\hat{\pi}$.



(a) True Positives (b) True Negatives

Fig. 3 An alternative presentation of the information in the ROC plot comparing the performance of the different estimators on the 1988 sample data. The standard logit model (dotted line) always performs worse than the autologistic model, for both true positives and true negatives.

Table 4 Out-of-sample forecasts

	Observed	
Predicted	*No*	*Yes*
No	62	21
Yes	27	29

Note. MCMC estimates from 1988 data are used to predict conflict over the decade from 1989 through 1998. No updating of exogenous data is undertaken. There are 29 successful conflict predictions and 62 successful predictions of no conflict.

Out-of-sample forecasts, or asking how well this simple technique can predict, provide a metric of performance far more compelling than relying on statistical significance alone. Our results show that the autologistic model holds considerable promise for empirical models that can help us understand how conflict processes evolve in the international system.

More specifically, we take the predicted results from the simulation using the estimated MCMC parameters for 1988 ($\hat{\theta}$) along with the data on democracy and the regional average of democracy for 1988 to *predict* the state of conflict in the subsequent decade. We are basically predicting whether a state will participate in a domestic or international conflict in the next 10 years, based on knowledge about the current state of conflict participation in all countries and whether they are democracies or autocracies in 1988. Thus, we do not allow the prediction to capitalize on the changes in political structures that occurred post-1989 to bolster the accuracy of the predictions. Again, based on the density function, we use a cutoff value of 0.35. Table 4 displays the predictions for each country in the international system from the simulations against the wars that actually took place from 1989 through 1998.

As shown in Table 4, the 1988 MCMC estimates of the autologistic model and the observed 1988 data yield 29 successful predictions of conflict and 62 successful predictions of no conflict. The large proportion of correct predictions should be tempered by 21 actual conflicts that were not predicted, as well as 27 falsely predicted conflicts. One of these false positives, South Yemen or the People's Republic of Yemen, however, should probably be considered a correct prediction. South Yemen merges with North Yemen or the Arab Republic in 1990 and, thus, disappears from the sample. A civil war breaks out in Yemen 1994 when former South Yemen tries to secede.

Stated differently, the simple autologistic model estimated on the 1988 data correctly classifies about two-thirds of the data observed in the subsequent decade. More interestingly, it successfully classifies almost 60% of the conflict participants. This lends some credibility to our claim that the regional context provides important information about the prospects for war and peace and is not simply "fitting" to the peculiarities of a given sample.

The correctly classified conflicts are listed in Table 5.[12] Our model misses cases of war participation for Afghanistan, Canada, Cambodia, Colombia, Cuba, El Salvador, France, India, Italy, Morocco, Nicaragua, Peru, Philippines, Romania, South Africa, Sri Lanka, the United Kingdom, the United States, Vietnam, and Yugoslavia. Many of these are states that participate in wars outside their regional context, as was the case for many participants in the Gulf War.

[12]Some countries involved in war in the period did not exist in 1988 (e.g., Bosnia) and, as such, are not part of the prediction set.

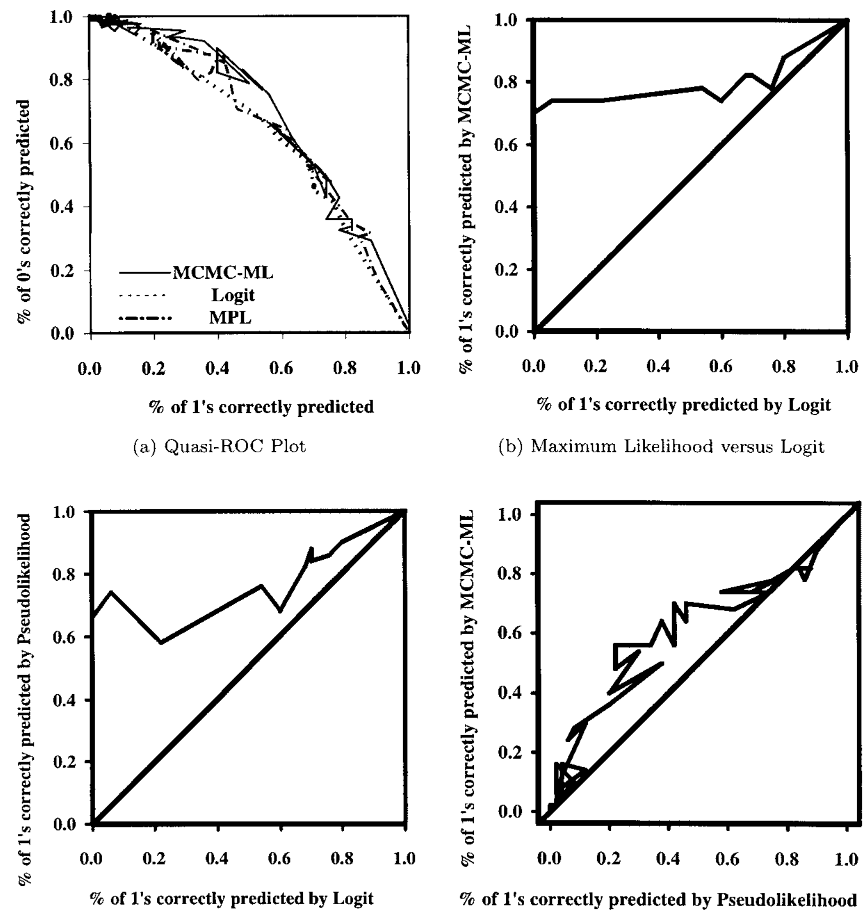
Table 5 Correctly predicted conflicts using 1988 data

Country	*Type*	*Onset*
Algeria	Civil	1993
Angola	Civil	1975, 1992
Bahrain	International	1991
Burundi	Civil	1988, 1991, 1998
Cambodia	Civil	1979
Congo—Brazzaville	Civil	1997
DRC—Zaire	Civil	1997
Egypt	International	1991
Ethiopia	International	1998
Guinea–Bissau	Civil	1998
Iraq	Both	1991
Kuwait	International	1991
Lebanon	Civil	1975
Liberia	Civil	1992
Mozambique	Civil	1975
Nigeria	Civil	1992, 1994, 1996
Oman	International	1991
Qatar	International	1991
Russia	Both	1979, 1991, 1995
Rwanda	Civil	1990, 1998
Saudi Arabia	International	1991
Sierra Leone	Civil	1998
Somalia	Civil	1982
Sudan	Civil	1995
Syria	Both	1991
Tanzania	Civil	1985
Turkey	Civil	1991
United Arab Emirates	International	1991
Yemen	Civil	1994
Zimbabwe	Civil	1984

Note. Both civil and international conflicts are predicted, including new and ongoing conflicts.

Not all of the 29 correctly classified conflicts involve new *outbreaks* or conflicts starting in the subsequent decade, since some of these conflicts were already under way in 1988, or earlier. Nonetheless, using data and information on conflict in 1988, our model identifies 17 new conflicts starting in the period 1989 to 1998 in addition to the 12 that had started by 1988 or earlier. Finally, we predict conflict for five countries that were involved in conflicts that terminated in 1988.

It is not realistic to expect that a simple autologistic model with limited unit-specific covariates should correctly predict *all* conflict during a subsequent decade, including participation in conflicts outside a state's regional context. Our data contain information only about a state's participation, not whether conflict was fought on the state's territory. Our model does not distinguish between types of states and does not attempt to identify why some states may be willing to engage in conflict elsewhere in the international system. The fact that this simple model does so well establishes that an autologistic modeling approach to conflict has substantial potential as well as providing a plausible starting point for subsequent research.



(a) Quasi-ROC Plot

(b) Maximum Likelihood versus Logit

(c) Pseudo-Likelihood versus Logit

(d) Maximum Likelihood versus Pseudo-Likelihood

Fig. 4 ROC plots comparing the 1989 to 1998 out-of-sample forecast for the different estimators for each value of $\hat{\pi}$, based on 1988 conflicts and 1988 values for exogenous variables. The MCMC maximum likelihood (ML) results dominate the results for MPL and logit.

Figure 4 displays ROC curves indicating how well the 1988 estimates and data *predict* conflict in 1989 to 1998 data, using the standard logit and the MCMC and MPL estimates as well as demonstrating the comparison of the MCMC maximum likelihood and MPL approaches with the logit approach. Again, the MCMC estimates of the autologistic dominate the standard logit. The MCMC estimates also perform much better than the pseudolikelihood estimates in the out-of-sample forecast. There is less difference among these three approaches at high $\hat{\pi}$ thresholds or values of C where conflict is predicted in nearly all states, resulting in a high number of correctly predicted conflicts (true ones) but a low number of predicted nonconflicts (true zeros). Such threshold values, however, obviously have rather limited practical relevance.

The 1988 estimates fail to predict conflict in about one-third of the cases in the 1989 to 1998 period. Using a more conservative threshold of $\hat{\pi} = 0.4$, we successfully predict fewer (11) conflicts along with many fewer (five) false positives.

The current model is preliminary, containing but a single covariate. It should be seen mainly as demonstrative of the power of locational covariation. It is based on statistical information gleaned from a single year, a year that occurred before a major transformation of international politics. The evolution of hostility and conflict over time as well as other factors known to affect the likelihood of conflict should be explicitly incorporated for a more realistic formulation. Despite these limitations, however, our out-of-sample forecasts can be viewed as an especially hard task to accomplish. Not only did we forecast across a sea change in international politics, we did so without updating the values of the independent variable within the forecast period. Given the simplicity of the covariates in the model estimated here and the difficulty of the test, we are encouraged by the results of this approach, which we hope can be annealed with additional tests in different time frames and ultimately improved by the inclusion of additional aspects that may indicate the known risks to peace that countries confront.

To our knowledge this effort is unique in successfully bringing proximity and interaction into a predictive mode for a large number of cases outside of the dyadic framework. Our results demonstrate that recognizing that all international actors are not independent still permits considerable statistical investigation of the patterns of international conflict. These results seem promising but should not be considered as evidence that we can reliably forecast war and turmoil with a low degree of uncertainty. But to our knowledge, its success rate in making out-of-sample forecasts of conflict, *ex post ante*, comes closer to that goal than most other published studies.[13]

7 Conclusion

International relations proclaims to study the interdependence of the forces in world politics, especially countries and organizations. However, virtually all scholarship that is statistically based has made the assumption that all countries are exchangeable (Ward 1988) and that the relevant data are statistically independent. Researchers have largely overlooked the mismatch between the strong evidence of interdependence in international interactions and the assumptions underlying our statistical conventions. Whether we want to take better advantage of predictive models or to inform better our empirical assessment of hypotheses, it is imperative to incorporate interdependencies and to take seriously the conditional dependence of our observed data. Our research here illustrates the importance of interdependencies and demonstrates some techniques that can allow us to take advantage of them in future work.

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[13]Other than the previously mentioned work of King and Zeng, there have been few efforts at out-of-sample forecasting. Schrodt (2000) reports one other line of research, using hidden Markov models, that has been used to predict levels of conflict in the Balkans. This effort involves true prediction and correctly predicts about one-quarter of the out-of-sample, high-conflict weeks. Of studies focusing on predicting conflict between pairs of countries (i.e., dyads), Beck et al. (2000) is the most successful. We compared our results for 1988 to their predictions and found little overlap between the conflicts they would predict and those that are correctly predicted in the current study. In 1988, if we set their $\hat{\pi}$ threshold to 0.35, i.e., the same as ours, they correctly predict the onset of four militarized *interstate* disputes in 1988: the United States and Iran ($\hat{\pi} = 0.39$), Myanmar and Thailand ($\hat{\pi} = 0.61$), Honduras and Nicaragua ($\hat{\pi} = 0.37$), and China and Vietnam ($\hat{\pi} = 0.70$).

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