Monthly Predictions of Conflict in 167 Countries, March 2015

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Every month, predictions are generated using the CRISP model. Currently, CRISP forecasts rebellion, insurgency, ethnic and religious violence, as well as domestic and international crises. The predictions identify onsets, as well as ongoing conflicts, and also provide estimates of the intensity of these events. To do so we construct (at least) three kinds of models for each event of interest. These models have a monthly time frame, and are applied to a population of 167 countries around the world. These include 1) an ensemble hierarchical model of whether an event of interest is present, 2) a count model of the number of incidences of conflict related to the event of interest, and 3) a split duration, event based model that generates an independent estimate of the onset of new events. This report highlights some of these predictions, made based on data up until February of 2015. Herein the actual models are very briefly discussed. Instead, focus is on predictions of continuations and onsets of these five classes of events.

CRISP is a suite of programs to aid CRISis Predictions. This report was created with CRISP package and the crisp.data.package version 2015.4.6

For the ICEWS data, see Boschee, Lautenschlager, O'Brien, Shellman, Starz, and Ward (2015): "ICEWS Coded Event Data", *Harvard Dataverse:* http://dx.doi.org/10.7910/DVN/28075 and Lautenschlager, Shellman, and Ward (2015): "ICEWS Event Aggregations", *Harvard Dataverse:* http://dx.doi.org/10.7910/DVN/28117

Insurgencies are defined as armed domestic engagements in which the goal of the insurgent groups is to replace the current authorities.

Insurgencies are often part, but not all, of civil wars. A good example of an insurgency is the current situation in Afghanistan.

The ensemble model averages predictions of eight different hierarchical models. Each hierarchical model consists of variables capturing a certain "theme" and uses two levels. One is a random effect for each country based on the extent to which groups are excluded from normal political participation as well as how democratic the governance structure is. This turns out to be very important. The second level comprises the so-called fixed effects for all countries. They are variables relating to the particular theme, for example indicators of democracy and autocracy in the "Politics" theme. The predictions for each component model are combined using Ensemble Bayesian Model Average (EBMA) techniques. This model has an in-sample Brier score of 0.03 and out-of-sample Brier score of 0.05. We can visualize the model fit with in and out-of-sample separation plots:

The eight themes are: Economy, Demographics, Politics, Infrastructure, Behavior of Insurgent Groups , Behavior of Government and Opposition Groups, and two themes capturing conflict dynamics in neighboring or otherwise similar countries.

Montgomery, Hollenbach, and Ward (2012): "Improving Predictions Using Ensemble Bayesian Model Averaging" *Political Analysis* 20 (3): 271-291.

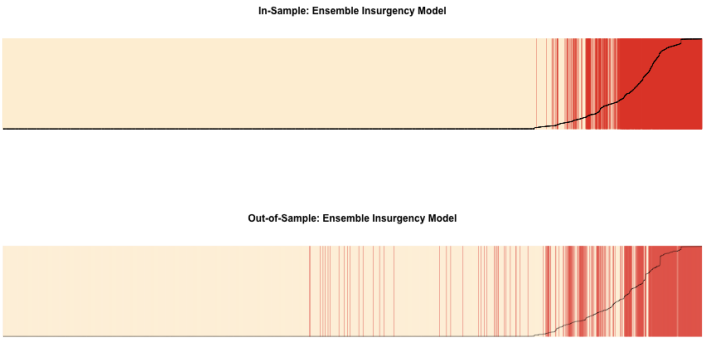


Figure 1: Ensemble model separation plots. The top plot shows the in-sample fit, with events indicated by red-hued lines. Country months without an event are lightly colored. The dark line is the predicted probability, which serves to sort the cases.

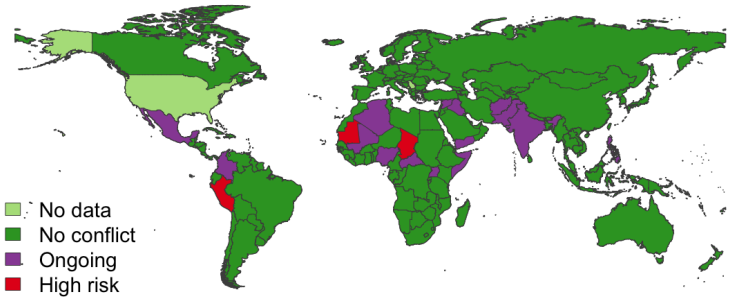
Those countries not currently experiencing an insurgency and with the predicted probability of having an insurgency being greater or equal to 0.5 are included in Table 1. Of all countries with predicted probabilities greater than 0.5, the cases with ongoing insurgency in February of 2015 are displayed in Table 2. These are currently considered to have insurgencies that are likely to continue; the other cases (shown in Table 1) are to be considered at risk for the onset of insurgency. The accompanying map shows those countries with ongoing insurgencies as of February 2015 and predicted probabilities larger or equal to 0.5 in purple. High risk countries with predicted probabilities equal to or above 0.5 for March 2015 are shown in red.

Table 1: Predicted Probabilities for Insurgency Onset, March 2015

	Country	Probability
1	Peru	0.99
2	Mauritania	0.92
3	Chad	0.80

Table 2: Ongoing Insurgencies, March 2015

	Country	Probability
1	Somalia	0.99
2	Afghanistan	0.99
3	Algeria	0.99
4	Philippines	0.99
5	Colombia	0.99
6	Iraq	0.99
8	Yemen	0.99
9	Pakistan	0.99
10	Central African Republic	0.98
11	India	0.95
12	Uganda	0.94
14	Mexico	0.91
15	Syria	0.88
16	Nigeria	0.80
18	Mali	0.78



THE SECOND APPROACH we use to predict insurgencies is a **split-population duration** model. Standard duration models estimate the

risk of failure for a state given how much time has passed since the last insurgency, and specifically how that risk evolves over time. This class of models was originally developed in the health and medical fields to model the survival of patients in terms of how much time can be expected to pass until some event of interest. We can similarly use them here to model the time until we can expect a state to experience an insurgency.

Table 3 reports the probability of conditional failure for the top ten countries in the risk set, i.e., those with non-zero risk, which are also shown in the accompanying map.

Table 3: Predicted Probability of Insurgency in a single month, using split-duration model.

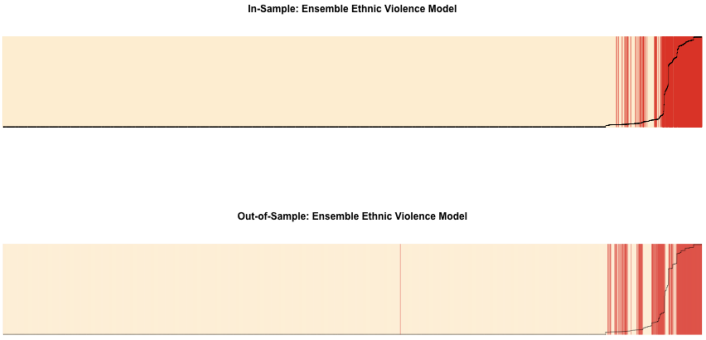
	Country	Probability
1	DR Congo	0.022
2	Bangladesh	0.013
3	Niger	0.012
4	Philippines	0.01
5	Kenya	0.009
6	Uganda	0.009
7	Burundi	0.008
8	Yemen	0.008
9	Syria	0.008
10	Sudan	0.008

Ethnic and Religious Violence is defined as violence among religious and ethnic groups, and excludes violence that involves governmental forces. There were 22 months of ethnic and religious violence in 2015, through February. Afghanistan has many episodes in its history of one tribal group engaging in violence against another. Rwanda, the Democratic Republic of the Congo, Yemen, Nigeria, and many other countries exhibit the same patterns. Recently, for example, in early 2014, anti-Muslim violence in Thailand has been on the upswing, despite the government's pledge to protect religious and ethnic minorities. As a base-level model we use an ensemble of hierarchical mixed effects models. Because there are so many country-months that do not experience ethnic and religious violence, the model is very good at predicting the absence of conflict; but it actually is also pretty strong at predicting ethnic and religious violence with very few false negatives.

Ethnic and Religious Violence excludes conflicts with the government.

This model has an in-sample Brier score of 0.01 and out-of-sample Brier score of 0.03. We can visualize the model fit with in and out-of-sample separation plots:

Those countries not currently experiencing an episode of ethnic vi-



olence but which have a predicted probability greater than or equal to 0.15 of experiencing an episode are included in Table 4. Of all countries with predicted probabilities greater than 0.15, the cases with ongoing ethnic violence in February of 2015 are displayed in Table 4. These are considered to have ongoing ethnic violence that is likely to continue; the other cases (shown in Table 5) are to be considered at risk for the onset of violence within or between ethnic and religious groups. The accompanying map shows those countries with ongoing episodes of ethnic violence as of February 2015 and predicted probabilities larger or equal to 0.25 in purple. High risk countries with predicted probabilities equal to or above 0.15 for March 2015 are shown in red.

Table 4: Predicted Probabilities for Ethnic Violence Onset, March 2015

	Country	Probability
1	Indonesia	0.94
2	Sri Lanka	0.92
3	India	0.73

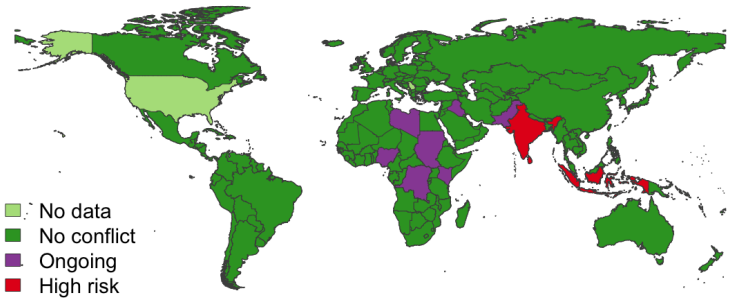


Table 5: Ongoing Ethnic Violence, March 2015

	Country	Probability
1	Nigeria	0.99
2	Kenya	0.99
3	DR Congo	0.99
4	Pakistan	0.99
5	Iraq	0.99
6	Sudan	0.98
10	Libya	0.41

THE SECOND APPROACH we use to predict ethnic violence is a **split-population duration** model. Once again, we note that standard duration models estimate the risk of failure for a state given how much time has passed since the last episode, and specifically how that risk evolves over time. This class of models was originally developed in the health and medical fields to model the survival of patients in terms of how much time can be expected to pass until some event of interest. We can similarly use them here to model the time until we can expect a state to experience an episode of ethnic violence.

Table 6 reports the probability of conditional failure for the top ten countries in the risk set, i.e., those with non-zero risk, which are also shown in the accompanying map.

Table 6: Predicted Probability of Ethnic Violence in a single month, using split-duration model.

	Country	March 2015
1	Pakistan	0.014
2	Yemen	0.009
3	Sri Lanka	0.005
4	Eritrea	0.004
5	Nigeria	0.004
6	Israel	0.003
7	Somalia	0.003
8	Turkey	0.002
9	Iraq	0.002
10	Sudan	0.002

Rebellions are violent internal conflicts which aim at creating a new polity by separation from the existing government in control of a particular geography. The new country of South Sudan is an example of such a successful rebellion, but rebellions exist in many other places around the world. The Palestinia Intifada of the early part of this century is another example. Obviously, rebellions, insurgencies, and ethnic violence may look similar in terms of some of their behavioral characteristics, but each is viewed as a separate kind of domestic violence in terms of CRISP models.

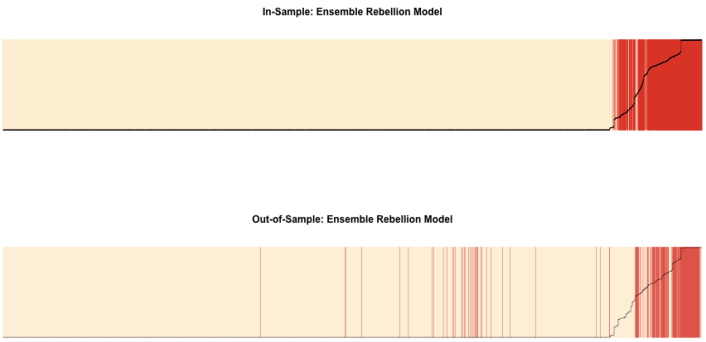


Figure 2: Ensemble model separation plots. The top plot shows the in-sample fit, with events indicated by red-hued lines. Country months without an event are lightly colored. The dark line is the predicted probability, which serves to sort the cases.

Those countries not currently experiencing an rebellion and with the predicted probability of having an rebellion being greater or equal to 0.5 are included in Table 7. Of all countries with predicted probabilities greater than 0.5, the cases with ongoing rebellion in February of 2015 are displayed in Table 8. These are currently are considered to have rebellions that are likely to continue; the other cases (shown in Table 7) are to be considered at risk for the onset of rebellion. The accompanying map shows those countries with ongoing rebellions as of February 2015 and predicted probabilities larger or equal to 0.5 in purple. High risk countries with predicted probabilities equal to or above 0.5 for March 2015 are shown in red.

Table 7: Predicted Probabilities for Rebellion Onset, March 2015

	Country	Probability
1	Senegal	0.99
2	Angola	0.92
3	Iran	0.91
4	Indonesia	0.86
5	Spain	0.82
6	Sri Lanka	0.79

Table 9 reports the probability of conditional failure for the top six countries in the risk set, i.e., those with non-zero risk, which are also shown in the accompanying map.

Table 8: Ongoing Rebellions, March 2015

	Country	Probability
2	Philippines	0.99
3	Sudan	0.99
4	India	0.99
5	Russian Federation	0.99
6	Myanmar	0.98
7	Pakistan	0.96
10	Turkey	0.87
14	Thailand	0.79

Table 9: Predicted Probability of Rebellion, using split-duration model.

	Country	Probability
1	Philippines	0.035
2	Yemen	0.02
3	Pakistan	0.014
4	India	0.011
5	Myanmar	0.007
6	Bangladesh	0.006
7	Ethiopia	0.006
8	Ukraine	0.006
9	Kenya	0.005
10	Nepal	0.004

Crises, Domestic and International are hard to define, but like power and pornography everybody seems to know them when they see them. These two variables are a bit complicated as well as controversial and are under some current development. As a result, the models for them are more preliminary than for other dependent variables, and herein only basic results are presented. The models that have been developed are less precise and accurate than those for specific forms of internal conflict discussed above. Domestic crises span a wide range of situations. The countries at risk of an new domestic crisis are given in Table 10.

Similarly, international crises are those involving more than one country, but at present the models are country models and do not involve interactions explicitly. So while the models can predict an international crisis, they do not predict the with with other country or countries the crisis involves. Predicted international crises are reported in Table 11.

Table 10: Predicted Probabilities for Domestic Crisis Onset, March 2015

	Country	Probability
1	Bolivia	0.99
2	Argentina	0.95
3	Peru	0.91
4	Paraguay	0.78
5	Greece	0.77

Table 11: Predicted Probabilities for International Crises Onset, March 2015

	Country	Probability
1	Bangladesh	0.92

PROTEST Lastly, we provide a predictive model for popular protest events using a count model. Table 12 shows the predicted number of protest events for the ten countries with the highest number of predicted events for March 2015. Moreover, the map depicts the predicted number of protest events for all countries divided into four bins.

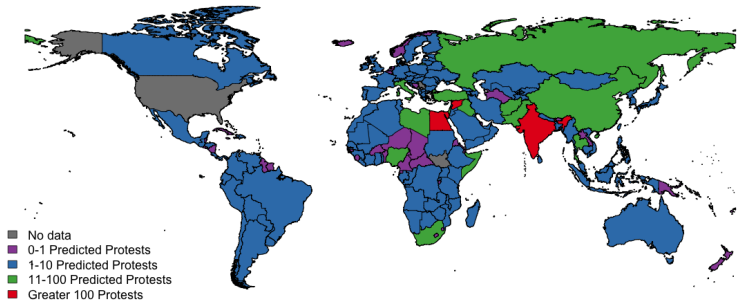


Table 12: Predicted Number of Protest Events, March 2015

	Country	Prediction
48	Egypt	6042.99
147	Syria	946.26
71	India	401.01
115	Pakistan	85.45
1	Afghanistan	66.76
126	Russian Federation	45.74
90	Libya	21.75
154	Turkey	19.95
33	China	17.26
150	Thailand	16.39

Additional information may be found at `mdwardlab.com` **and** `predictiveheuristics.com`**.**