Article

Supplement to Bayesian Spatial Models for Projecting Corn Yields

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1. Results with PICAR mesh and density selected using AIC

In this section, we compare the predictive performances of the models considered. We report results from the most computationally efficient PICAR model as the results from the slower PICAR model are nearly the same. We relegate the results from the slower PICAR model to the supplement. We also compare their performances in reducing spatial correlation of the residuals. Finally, we compare the projections from these models for the near future and end-of-century projection periods.

1.1. Variable Impacts

We first consider the fit relationships between the weather variables of interest, precipitation and temperature, and corn yield. In Figure S1, on the left we display the impact of an additional hour of exposure to each temperature (°C) during the growing season on yield (bushels/acre). We see a similar relationship between heat exposure and temperature as found by [1], where exposure to temperatures between 10°C and 29°C has a weakly positive impact on yield, while exposure to temperatures above 29°C has a strongly negative impact on yield. In Figure S1, on the right we also see that increasing total precipitation up to around 0.8 L during the growing season has a decreasingly positive impact on yield, while total growing season precipitation above that level has an increasingly negative impact on yield. We display the relationships fit using the 0.05, 0.5, and 0.95 quantiles of the MCMC samples for the parameters characterizing the relationships between these weather variables and yield.

We also consider the impacts of the mean fit quadratic time trend by state from the historical period to the end of the 21st century. All statistical models give that impact of time on yield will on average be positive in both projection periods for all states (Figure S2). The estimated mean impacts of time on yield by state vary depending on the statistical model. We report these effects at the end of the century. The CI model gives the largest mean time effect in Georgia, increasing yield by 1393 bushels/acre, and the smallest mean time effect is in New Jersey, increasing yield by 317 bushels/acre. The PICAR (BIC) model gives the largest mean time effect in Georgia, increasing yield by 1381 bushels/acre, and the smallest mean time effect is in Indiana, increasing yield by 214 bushels/acre. The PICAR (BIC) model gives the largest mean time effect in Georgia, increasing yield by 1409 bushels/acre, and the smallest mean time effect is in Indiana, increasing yield by 246 bushels/acre. This can be interpreted as meaning the impact of technology and other unaccounted for temporal factors is positive long term in all states, and is strongest in Georgia.

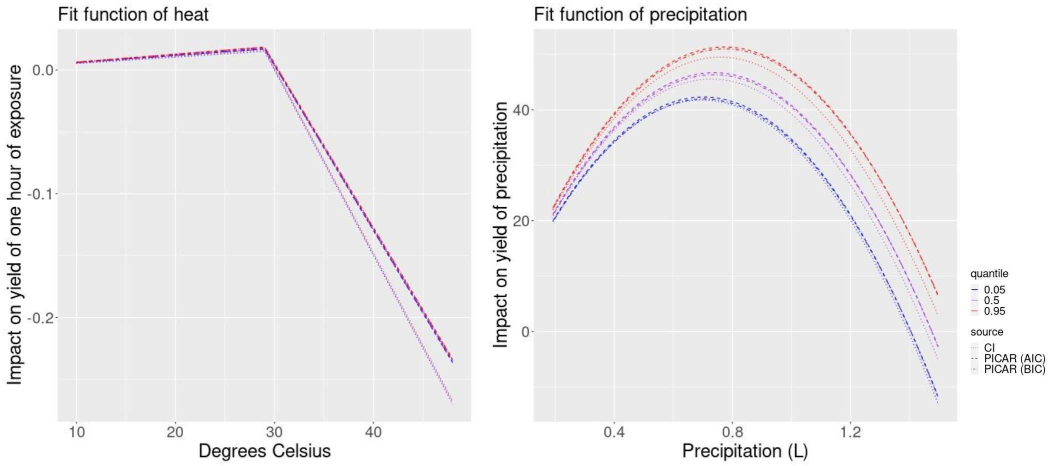

Figure S1. Fit relationship between heat exposure and yield with based on the middle 90% of MCMC samples of the coefficient posteriors

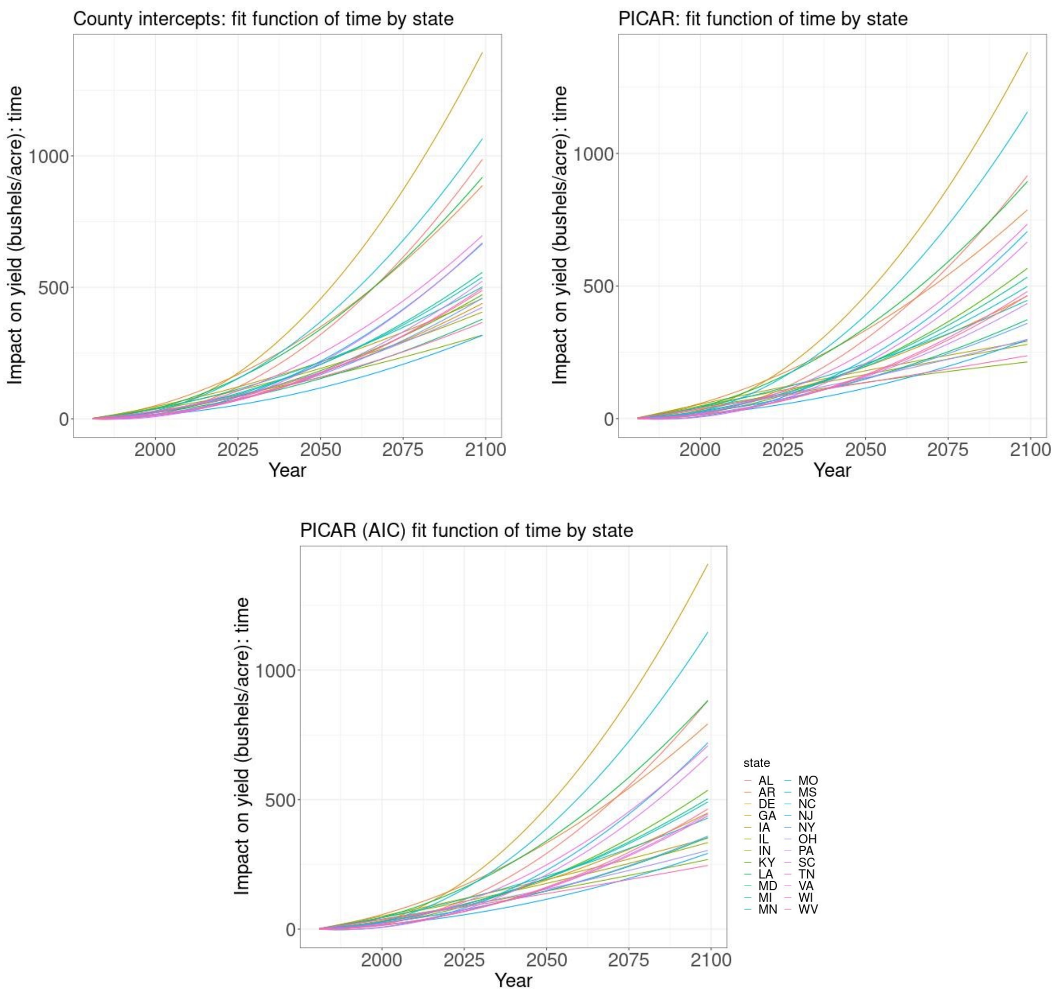

Figure S2. Fit relationships between time and yield for each state based on the means of the coefficient posteriors

1.2. Predictive Performance

We compare the performances of the county intercepts (CI) model to the PICAR models based on root mean-squared error (RMSE), mean absolute error (MAE), and prediction interval coverage on four years of held out data (2015-2018). We select these years as the held out data because we are interested in using our model to project corn yields in future years. In general, all models perform adequately for prediction. For all models, the median distance of the prediction to the observation is less than 10% of the value of the observation. We display a table containing the root mean squared errors and mean absolute errors for each approach. Here, PICAR (AIC) denotes the PICAR model with rank of Moran's basis function matrix and mesh density selected using AIC, and PICAR (BIC) denotes the PICAR model with rank of Moran's basis function matrix and mesh density selected using BIC (Table S1). CI indicates the county intercepts model. Overall, the CI model with more covariates has slightly increased predictive ability compared to the PICAR models considering the scale of the data values (Table S1). The CI model has RMSE of 21.2 bushels/acre and MAE of 16 bushels/acre; the PICAR (BIC) model has RMSE of 24.9 bushels/acre and MAE of 19.4 bushels/acre, and the PICAR (AIC) model has RMSE of 25 bushels/acre and MAE of 19.3 bushels/acre. For scale, 25 bushels/acre is lower in value than 99% of all observed yields. Side-by-side boxplots illuminate the distribution of the prediction errors from each approach (Figure S3). The distribution of errors is approximately symmetric around zero for all models. However, there generally are more cases of predictions that are much too high than much too low.

While the CI model has slightly improved predictive performance over the PICAR models, the PICAR models take much less time to approximate a large enough posterior sample. The PICAR (BIC) model has a mean effective sample size (ESS) per second of 151 and a minimum ESS/second of 48.2. The PICAR (AIC) model has a mean ESS/second of 39.6 and a minimum ESS/second of 9.74. Meanwhile, the county intercepts model has a mean ESS/second of 2.98 and a min ESS/second of 2.66. So the computational efficiency gained by using a PICAR model is huge, especially when the rank of Moran's basis function matrix and mesh density is selected using BIC rather than AIC. To minimize BIC, we selected a lower rank and sparser mesh density than to minimize AIC. Since the predictive abilities of the PICAR (BIC) and PICAR (AIC) models are nearly indistinguishable and the PICAR (BIC) approach is faster, we deduce that using BIC for rank and mesh density selection is preferable.

Table S1. Predictive performance on held out years

	CI	PICAR (BIC)	PICAR (AIC)
RMSE	21.2	24.9	25.0
MAE	16.0	19.4	19.3

1.3. Performance in Accounting for Spatial Correlation

We also consider the performance of these models in terms of their reduction of spatial patterns in the residuals. For the four held out years of data, we display the observed minus the predicted crop yield. In general, between the CI, PICAR (BIC), and PICAR (AIC) models the spatial patterns in the residuals are similar, but the yields that are predicted to be too high tend to be a bit higher for both PICAR models. For 2015, the lingering spatial patterns in the residuals are similar across all models, but the yields that are predicted to be too high tend to be a bit higher for the PICAR models. For 2016 and 2017, the same is true. For 2018, the same is again true except in parts of Iowa the tendency to predict too small of yield is more extreme for the CI approach, and in a few other counties with too low of a predicted yield, this prediction is more extreme for the PICAR approaches. Between the two PICAR approaches, the plots of the residuals in space are very similar across all years.

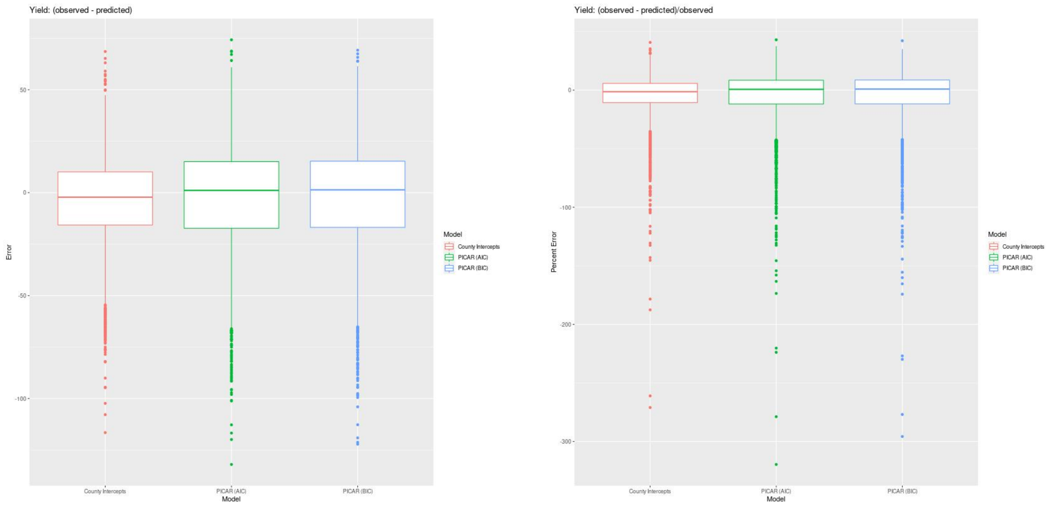

Figure S3. Distribution of prediction errors from the CI, PICAR(BIC) and PICAR (AIC) models

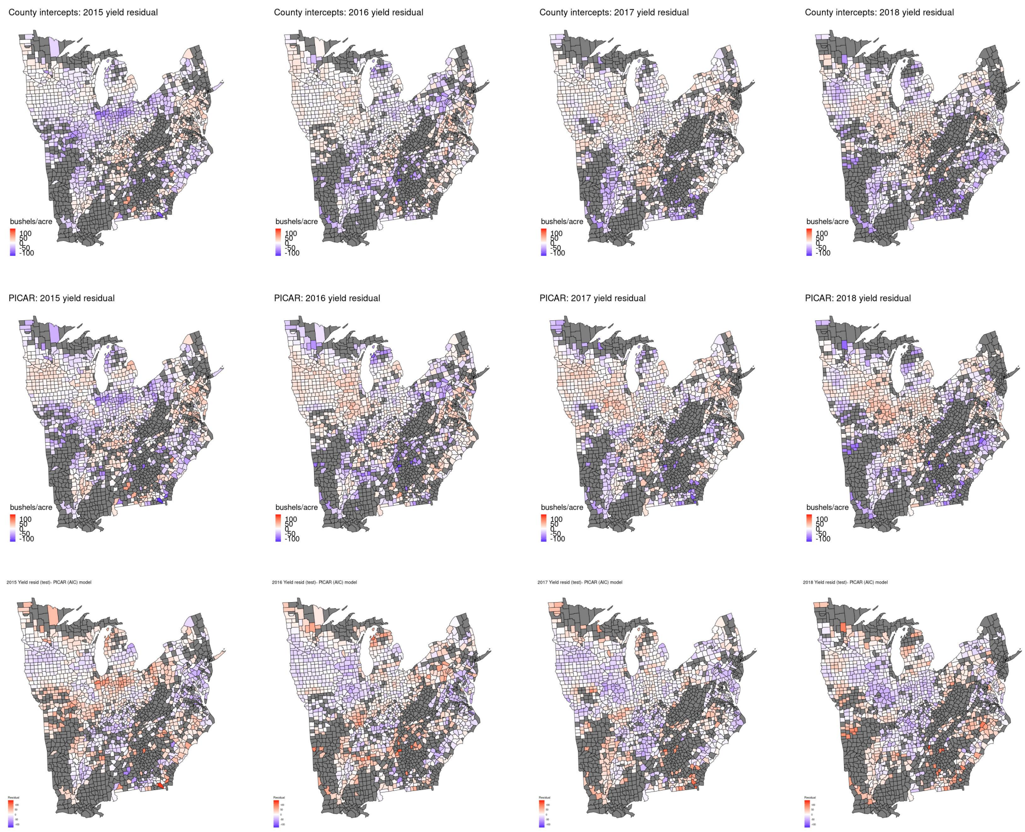

Figure S4. Residuals in space for each held out year (2015-2018) with the CI model (top row), PICAR (BIC) model (middle row), and PICAR (BIC) model (bottom row)

References

1. Schlenker, W.; Roberts, M.J. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *PNAS* **2009**, *106*, 15594–15598.