

The probabilistic role of climate change on crop yield potential

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The findings and conclusions in these slides are those of the author and should not be construed to represent any official USDA or U.S. Government determination or policy.

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A Ricardian approach

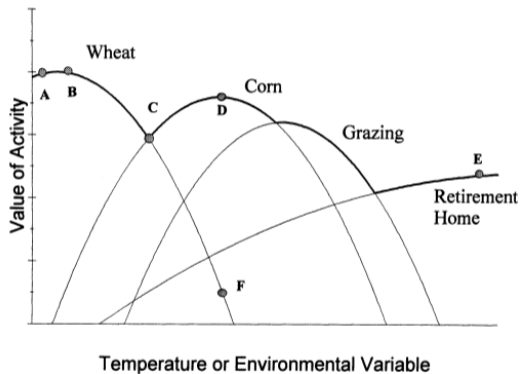


FIGURE 1. BIAS IN PRODUCTION-FUNCTION STUDIES

Source: Mendelsohn, Nordhaus, and Shaw's (1994) *The impact of Global Warming on Agriculture: A Ricardian Analysis*.

Popularity

Due to its simplicity, several studies report employing the *Ricardian approach* to estimate the impact of climate change on agriculture in different regions such as,

- Canada (Reinsborough, 2003),
- China (Wang *et al.*, 2009),
- Europe (Van Passel, Masseti, and Mendelsohn, 2016), and
- South Africa (Gbetibouo and Hassan, 2005).

(A few) Methodological limitations

Available methodologies have been proven to have limitations:

McIntonsh and Schlenker (2006),

- Do estimated parameters **reflect a long-run or short-run responses** to weather variations?

Deschenes and Greenstone, (2007),

- **A-temporal unobserved mechanisms** cannot be controlled for by the researchers.

Schlenker and Roberts (2009),

- The **relationship between crops' growth and heat** is highly non-linear.

Ortiz-Bobea (2020), and

- **Non-farm influences** have been growing in importance in the valuation of farmland prices.

Mérel and Gammans (2021).

- **Estimated parameters do not reflect long-run responses** to weather variations.

Bayesian formulation of the Ricardian approach

A Bayesian formulation of the Ricardian approach can circumvent several limitations that practitioners encounter when studying crop yields by incorporating model structure (Gelman, 2008; Gelman, Lee, and Guo, 2015; Van de Schoot *et al.*, 2021).

- Previous crop yield studies exploit the fact that **Bayesian inference does not depend on asymptotic approximations** (e.g., large number of observations).
 - Ozaki *et al.*, 2008 apply their methodology to Brasil, and
 - Ramsey (2020) combines a Bayesian framework with a quantile regression.
- My study constructs a Bayesian formulation that **integrates agronomic evidence** on the yield-weather interaction.
 - **Parametrizing the dependence between unit-level production and global parameters permits flexibility in the model design.**

Preview of results

Crop yield projections from Midwestern and Eastern U.S. counties for 2022, 2027, and 2032 indicate that,

- Soybean farmers in Midwestern counties will shift to corn production,
- Findings corroborate existing evidence regarding U.S. agricultural outlooks, and
- Short-term productivity gains are associated with the largest producers.

Posterior distributions: The math

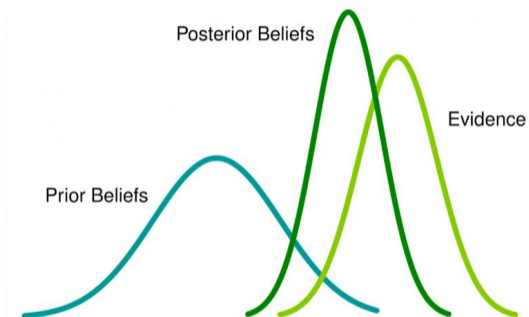
Posterior distributions are *sampled*, point estimates are *estimated*:

$$\underbrace{p(\theta_i | y_{it}, x_{it})}_{\text{Posterior}} \propto \underbrace{p(y_{it}, x_{it} | \theta_i)}_{\text{Likelihood}} \underbrace{p(\theta_i)}_{\text{Prior}}$$

where

- y_{it} denotes crop yield realizations,
- x_{it} denotes observed weather, and
- θ_i denotes estimate values.

Poserior distributions: The viz



Source: NSS (2016) *Bayesian statistics explained to beginners in simple English* in Analytics Vidhya.

Can we expand the probability?

A challenge of estimating posterior distributions is that *wide* distributions are unreliable (think about the trade-off between bias and variance).

$$\underbrace{p(\theta_i, \tau | y_{it}, x_{it})}_{\text{Posterior}} \propto \underbrace{p(y_{it}, x_{it} | \theta_i)}_{\text{Likelihood}} \underbrace{p(\theta_i, \tau)}_{\text{Prior // hyper-prior}}$$

where

- τ is a probabilistic structure *above* the priors.

Likelihood

I assume that farmer maximizes output by varying inputs as a function of variations in weather, $y_{it} \equiv \Psi(x_{it}, \gamma^*(x_{it}))$, and $\gamma^*(x_{it})$ is **optimal output employment as a response to observed weather**.

I propose a **Beta-type probability distribution** that builds upon the work of Nelson and Preckel (1989), and Cribari-Neto and Zeileis (2010):

$$B(\mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} \times \frac{y_{it}^{\mu\phi-1} (y_u - y_{it})^{(1-\mu)\phi-1}}{y_u^{(\phi-1)}}$$

where

- $1 > \mu > 0$ is the location parameter,
- $\phi > 0$ is the spread parameter, and
- y_u is an upper limit for crop yield realizations defined by the researcher.

Priors

I relate data on crop yield and weather observations with my **prior structures about the effect of weather on cropm yields.**

$$\ln\left(\frac{\mu}{1-\mu}\right) \sim N(\beta_i^{GDD} GDD + \beta_i^{EDD} EDD + \beta_i^{PPT} PPT + \Psi(t), \sigma)$$

where

- my weather variables of interest are GDD, EDD and PPT,
- $\Psi(t)$ is a temporal structure that controls for non-weather variation, and
- A link function, $g(\mu) : \mathbb{R} \mapsto (0, 1)$ to keep $B(\mu, \phi)$ well defined.

(A peak to the) Hyper-priors

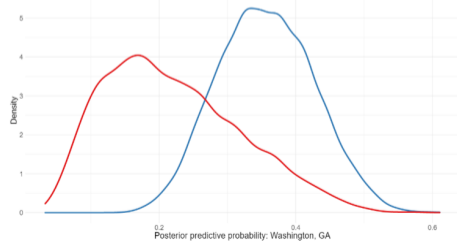
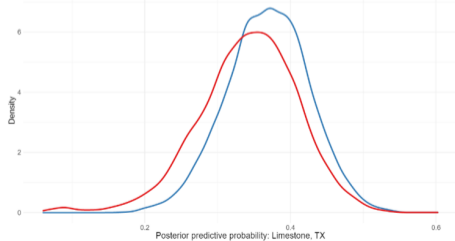
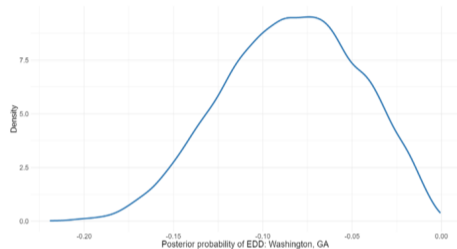
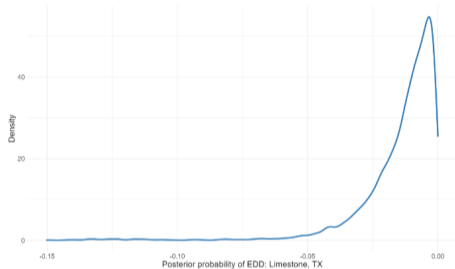
A variance-covariance matrix regulates the spatial and temporal effect of weather on crop yields.

$$\begin{pmatrix} \beta_i^{GDD} \\ \beta_i^{EDD} \\ \beta_i^{PPT} \end{pmatrix} \sim N(\mathbf{M}, \mathbf{\Sigma})$$

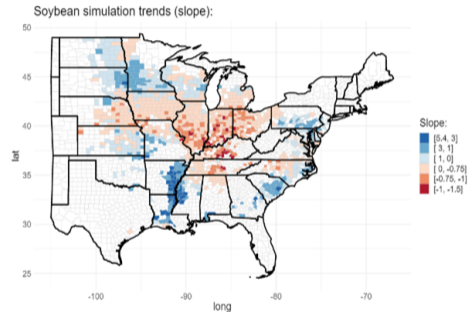
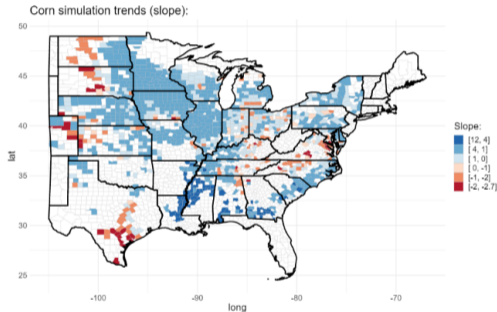
where

- \mathbf{M} is a vector of means, and
- $\mathbf{\Sigma}$ is a variance-covariance matrix.

Posterior distributions and example simulations



Corn and soybean yield trends in Midwestern and Eastern counties



Bayesian formulation:

Previous crop yield studies exploit the fact that **Bayesian inference does not depend on asymptotic approximations** (e.g., large number of observations),

My study constructs a Bayesian formulation that **integrates agronomic evidence** on the yield-weather interaction, and

Flexibility in the model design.

Results:

- Soybean farmers in Midwestern counties will shift to corn production,
- Findings corroborate existing evidence regarding U.S. agricultural outlooks, and
- Short-term productivity gains are associated with the largest producers.