Studying Climate Change Impacts from Different Methodological Perspective

Sponsoring sections (50% sponsorship each):

- Econometrics
- Agribusiness Economics and Management

The authors' perspectives to the study of climate change impacts

- **Noé J Nava**, USDA - Economics Research Service (A Bayesian perspective)
- **William C Ridley**, University of Illinois (A Meta-analysis perspective)
- **Matthew Gammans**, Michigan State University (An Econometrics perspective)
- **Jayson Beckman**, USDA - Economics Research Service (A General Equilibrium perspective)

The findings and conclusions in this article are those of the author and should not be construed to represent any official USDA or U.S. Government determination or policy. This research was supported in part by the USDA, Economic Research Service.

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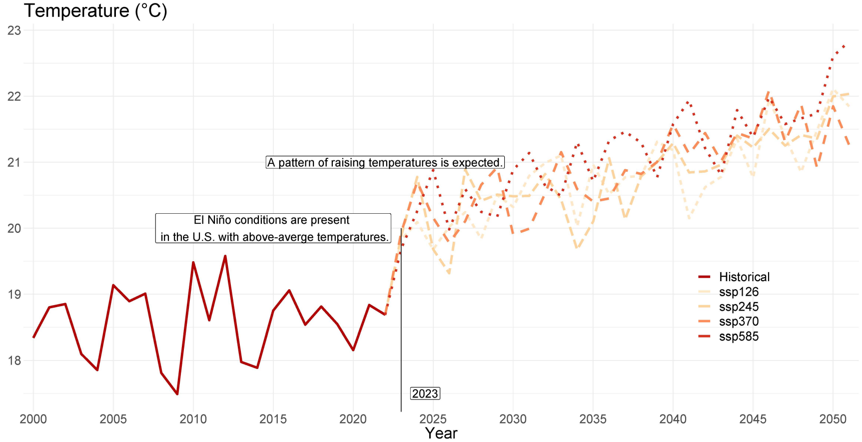
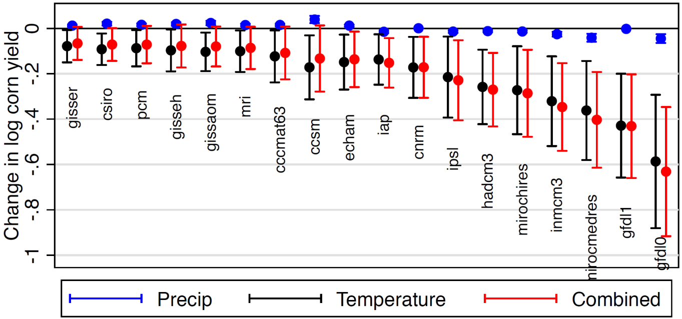


Source: Nava *et al.* (2023) *Agro-climatic patterns for the Corn Belt towards 2050*, Historical yields for U.S. corn and soybeans, 1970 to 2022. Data from Oregon University PRISM, and NASA's NEX-GDDP.

"Longer run adaptations appear to have mitigated less than half of the large negative short-run impacts of extreme heat on productivity."



Source: Burke and Emerick's (2016) *Adaptation to Climate Change: Evidence from U.S. Agriculture*, Productivity of Two Different Corn Varieties as a Function of Temperature.

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Heterogeneous Patterns of Crop Yield Growth Stagnation across U.S. Counties in the Next Decade

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AAEA 2023: Track Session - Studying Climate Change Impacts from Different Methodological Perspectives

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Suggestions from the literature on options for reducing climate impacts on agriculture

Efficient food consumption and production

- **Stronger local and regional food systems** to cope with supply chain disruptions that lead to waste (Thilmany *et al.*, 2021).
- **Promotion of local agriculture** can potentially reduce pressure on environmental endowments (Clapp, 2015).
- **Reducing food waste** can potentially reduce energy and resource consumption (Hall *et al.*, 2009).

Source: Photo by Christian Mackie on Unplash.

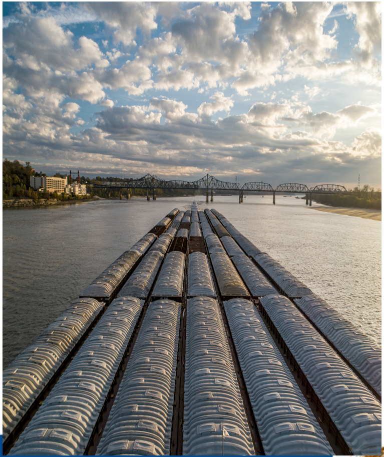
Suggestions from the literature on options for reducing climate impacts on agriculture

Increase productivity

- **Precision agriculture** can decreases input usage, pushing agricultural productivity upward (Balafoutis *et al.*, 2017).
- **Adoption of new technologies** that produce yield growth similar to Genetically Engineered seeds (Ortiz-Bobea and Tack, 2018).
- **Crops' drought and heat** tolerance (Lamaoui *et al.*, 2018).

Source: Photo by CHUTTERSNAP on Unplash.

Suggestions from the literature on options for reducing climate impacts on agriculture



Trade

- **Openess to trade** can potentially increase global grain supply (Zereyesus *et al.*, ongoing work).
- **Reliance on domestic trade** to find new sources of inputs (Dall'Erba, Chen, and Nava, 2021).
- Increasing regions' **import substitution capacity** (Nava, Ridley, and Dall'Erba, 2023).

Source: Photo by Justin Wilkens on Unplash.

- Study's goal:
  - Quantify the extent to which agricultural productivity (e.g., yields) will stagnate next decade.
  - Where in the U.S., we should expect patterns of stagnation.
- Findings (Robust to alternative assumptions about crop yield growth):
  - **Warming temperatures can potentially stagnate U.S. crop yield growth in 2032** with a probability equal or higher than 75%.
  - The largest productivity losses are associated with counties **in the Corn Belt**.

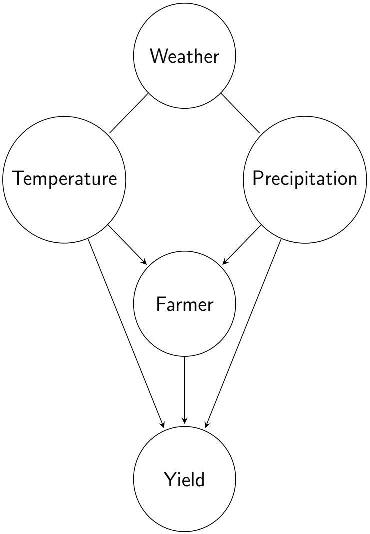
Value added of this paper

- Contrary to Artificial Intelligence (e.g., the new ML) applications, **Bayesian approaches maximize predicitive power without limiting causal interpretation**.
- Existing work only acknowledges **agro-economic** evidence about the interaction between weather variations and crop yield growth.
  - Growing degree days is found to be positive, and extreme degree days is found to be negative (Schlenker and Roberts, 2009).
- A **mathematically tractable probabilistic model** of the Ricardian approach, where most studies focus on frequentist approaches.
- A **Beta-type log-likelihood** that has the advantage of having a location and spread parameters (similarly to commonly used normal distributions) and cab be shown to be more efficient in the study of crop yields.

A **Hierarchical Bayesian** process employes a Hamiltonian Monte Carlo Markov-Chains (H-MCMC) algorithm that **samples** from:

$$p(\beta_i, \tau | y_{it}, x_{it}) \propto p(y_{it}, x_{it} | \beta_i) p(\beta_i, \tau) \qquad (1)$$

- Hyper-priors, τ:
  - $\lambda \sim Cauchy(0, 1)$
  - $\Omega \sim LKJ(\eta)$ and $\eta \in \{0.5, 1.0, 2.0\}$
  - $\sigma \sim N(0, 1)$ and $\phi \sim \chi^2_{25}$
- Priors, $\beta_i' = (\beta_i^{GDD}, \beta_i^{EDD}, \beta_i^{PPT})$:
  - $\beta_i \sim N(M, \Sigma)$
  - $M' = (0^+, 0^-, 0)$
  - $\Sigma = diag(\lambda)\Omega diag(\lambda)$
  - $\mu_{it} \sim N(X_{it}\beta_i + \Psi(t), \sigma)$
- Log-likelihood, $p(y_{it}, x_{it} | \beta_i)$:
  - $Beta(.) = \frac{\Gamma(\phi)}{\Gamma(\mu_{ij}\phi)\Gamma((1-\mu_{ij})\phi)} \frac{y_{it}^{\mu_{it}\phi-1}(y_u - y_{it})^{(1-\mu_{it})\phi-1}}{y_u^{\phi-1}}$



Conceptual framework

Farmers' output, y_{it}, is a function of their responses to variations in weather. That is,

$$y_{it} \equiv \Psi(x_{it}, \gamma^*(x_{it})) \tag{1}$$

Where:

- x_{it} is farmers' observed weather each time period t at location i; and
- $\gamma^*(x_{it})$ is input employment as a response to observed weather.

Therefore,

- $\Psi(x_{it}, \gamma^*(x_{it}))$ captures the diverse managerial responses to weather.

Modeling farmers' responses to weather variations

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

$$Beta(\mu_{it}, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu_{ij}\phi)\Gamma((1-\mu_{ij})\phi)} \times \frac{y_{it}^{\mu_{it}\phi-1}(y_u - y_{it})^{(1-\mu_{it})\phi-1}}{y_u^{\phi-1}} \tag{2}$$

where:

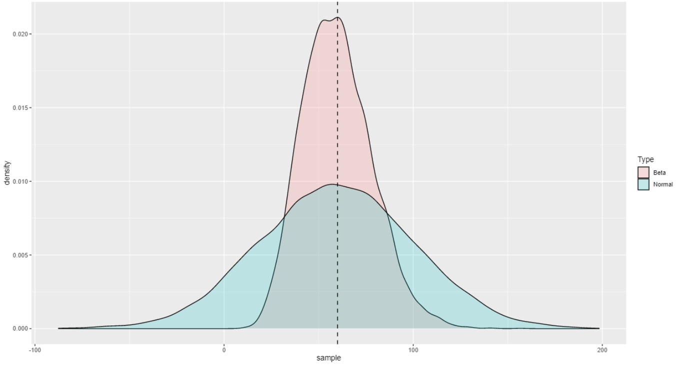
- $1 > \mu_{it} > 0$ is a parameter that controls the location of the distribution;
- $\phi > 0$ is a parameter that controls thhe dispersion of the distribution;
- y_u is an upper limit of the distribution set to $y_u = 300$; and
- $\Gamma(.)$ denotes the Gamma probability function.
- First moment $E[y_{it}] = \mu_{it} y_u$, and second moment $Var[y_{it}] = \frac{\mu_{it}(1-\mu_{it})}{1+\phi} y_u$.

Statistical story Econometric advantages

Towards a stochastic production model of crop yields

Because the Beta-type probability function has a range $(0, y_u)$,

1. Simulation draws and parametric interpretations are bounded; and
2. Parameter estimation is more efficient than normal distribution applications **(work in progress)**.



Note: rok-cesnovar has kindly created a dynamic illustration of my custom distribution in https://github.com/rok-cesnovar/stan-distributions.

To add flexibility in the type of modeled effects, the following priors are assumed:

- $\boldsymbol{\beta_i}$ is drawn from $N(\boldsymbol{M}, \Sigma)$, where $\boldsymbol{M'} = (0^+, 0^-, 0)$, such that:
  - Schlenker and Roberts (2009)
    - **GDD is assumed positive.**
    - **EDD is assumed negative.**
  - Li et al. (2019)
    - **PPT is uninformative.**
- The **combined effect of two weather variables is also accounted for** (Gelman and Hill, 2007):
  - $\Sigma = diag(\lambda)\Omega diag(\lambda)$.

$$\Omega = \begin{bmatrix} 1 & \rho_{G,E} & \rho_{G,P} \\ \rho_{EG} & 1 & \rho_{E,P} \\ \rho_{P,G} & \rho_{P,E} & 1 \end{bmatrix}$$

Simulation results: Structure

Following the work of Ortiz-Bobea and Tack (2018), I **assume two alternative retrospective treatments of crop yield growth** parametrized under $\Psi(t)$, previously described:

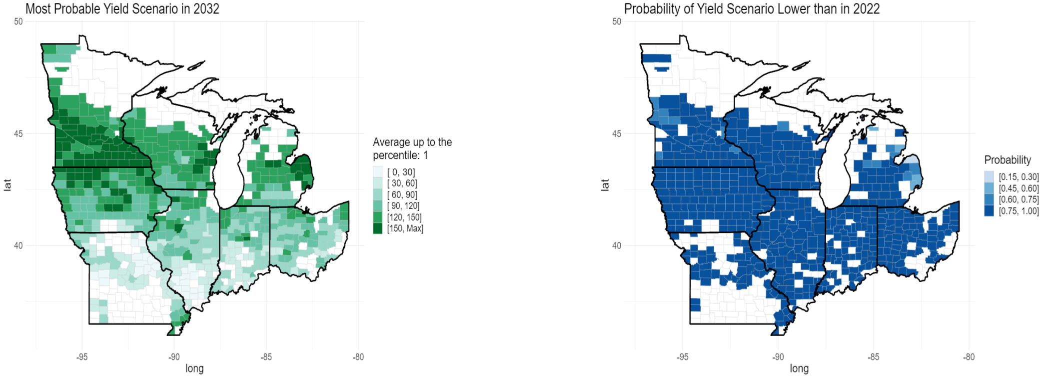
- **No-growth regime** assumes stagnation based on 2017 data and acts as **lower-limit**.
- **Pre-trend regime** assumes same trend between 1992-2017 and acts as an **upper-limit**.

Simulations are intended to **study stagnation patterns**:

- Trend analysis focuses on slopes of trend between 2022-2032.
- Probabilistic concluding remarks.

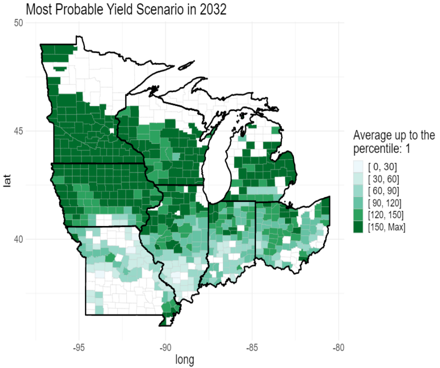
Post-estimation simulations are produced taking into **consideration heterogeneity of posterior distributions**.

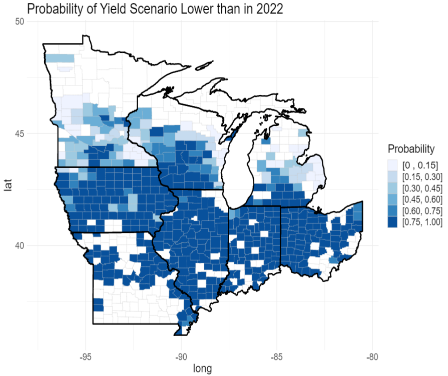
Corn simulations under no growth regime



Note: Left figure describes corn yield results for 2032. Right figure describes the probability of observing corn yield below ther 2022 output.

Corn simulations under pre-trend regime





Note: Left figure describes corn yield results for 2032. Right figure describes the probability of observing corn yield below their 2022 output.

Concluding remarks

A probabilisitc model of the interaction of weather variations and crop yield growth is developed to provide short-term corn and soybean projections for the United States.

- Model is parametrized to capture **farmers' short-run responses**;
- Prior and hyper-priors are imposed to **incorporate agronomic evidence** about the role of weather on crop yield growth; and
- A **Beta-type likelihood distribution** is developed to include parameters for location and spread.

Findings:

- **Warming temperatures can potentially stagnate U.S. crop yield growth in 2032** with a probability equal or higher than 75%.
- The largest productivity losses are associated with counties **in the Corn Belt**.

Thanks!