

Introduction

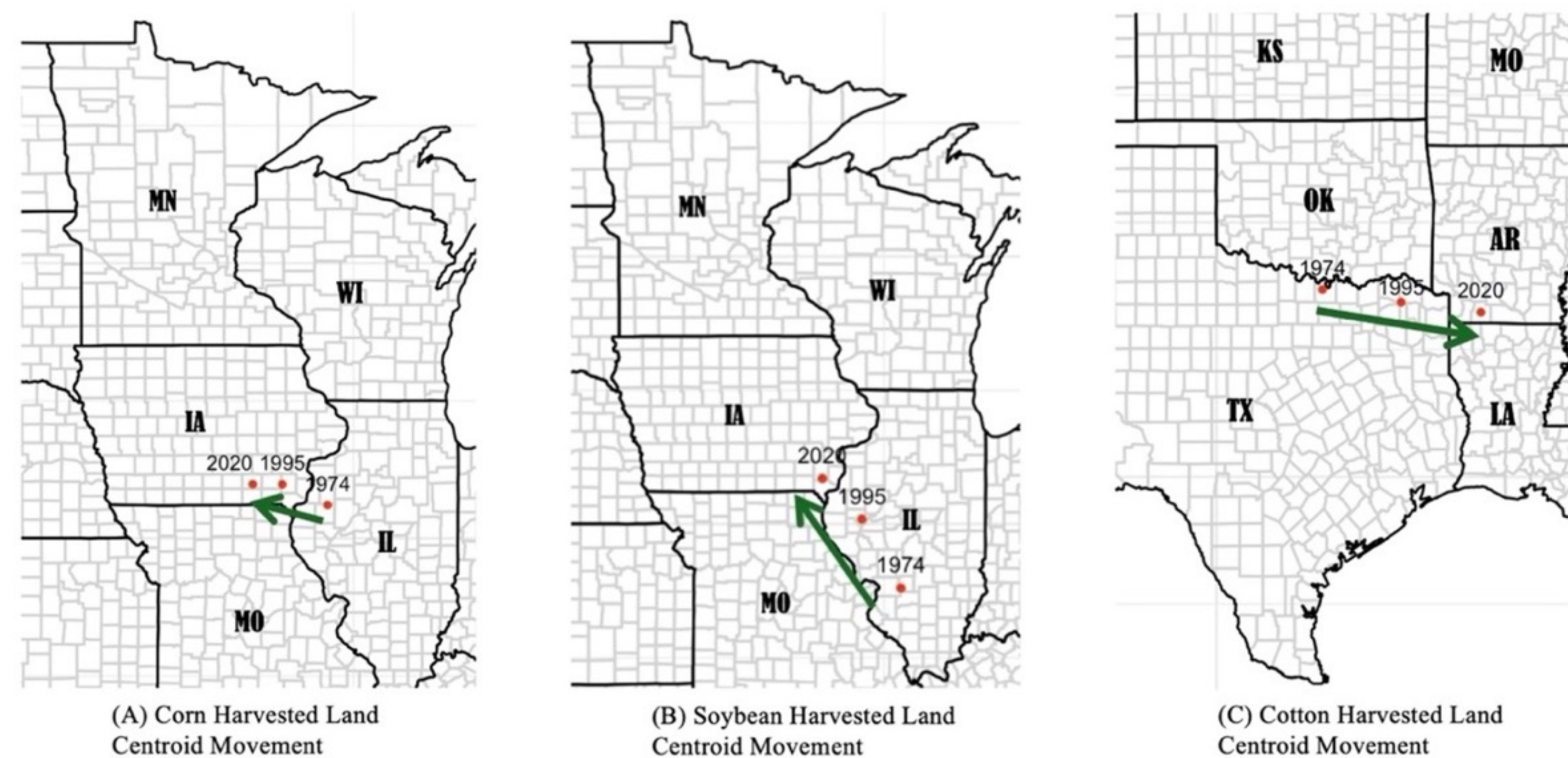
Genetic engineering (GE) is a key adaptation tool: it boosts yields and helps farms cope with heat, drought, shifting rainfall, and pests. As climate pressures intensify, growing-area suitability is changing, causing adjustments in management, crop mix, and land use. The sector needs scalable, evidence-based adaptation.

Bt/HT and newer drought/heat-tolerant traits have raised yields and profits in many trials and regional studies. But we still lack national, econometric evidence on how GE mitigates climate impacts on both mean yields and yield variability—and whether GE shapes long-run spatial production patterns. Filling this gap matters because geographic shifts carry large economic and ecological costs.

Since the 1970s, corn/soybean area has moved north/west while upland cotton has expanded east. Climate explains less than half of these shifts, pointing to technology as a driver. From 1974-1995 corn's centroid's latitude moved 40.601°→40.979° (62 miles) but only to 40.982° by 2020 (+36 miles); soybean moved 38.803°→40.090° (102 miles) from 1974 to 1995, then to 40.848° (+72 miles) by 2020 (Fig. 1). Patterns indicate GE adoption likely moderated northward displacement, especially by sustaining yields in warmer southern regions.

Objectives

In this study, we conduct a US national-level econometric and spatial analyses to quantify the impacts of genetically engineered (GE) crop adoption on 1). crop yield, 2). crop yield variation, 3). crop cultivation area and 4). the climate change sensitivity of crop production for corn, soybean and upland cotton.



Data source: USDA Quickstats; USDA NASS, annual June Agricultural Survey (1974-2020)

Figure 1. Crop Harvested Land Centroid Movement from 1974 to 1995 to 2020

Methods

- For yield and yield variation, we used a 3 stage Just and Pope model:

Stage 1: Estimate an equation for the mean of crop yield in log form as

$$\log(z_{mit}) = \delta_m x_{mit} + \sum_k \rho_{mk}^a W_{k^{a_{it}}} + \phi_m irri_{mit} + \lambda_m T_t + \gamma_m mills_{mit} + \zeta_{mi} + \epsilon_{mit} \quad \dots \text{for all } m$$

Stage 2: Estimate a function for the log of the variance of crop yield as

$$\log(\epsilon_{mit}^2) = A_m + \mu_m x_{mit} + \sum_k \sigma_{mk}^a W_{k^{a_{it}}} + \tau_m irri_{mit} + \varphi_m mills_{mit} + v_{mit} \quad \dots \text{for all } m$$

Stage 3: Estimate a heteroskedasticity adjusted mean function for log of crop yield

$$\frac{\log(z_{mit})}{\epsilon_{mit}} = \delta'_m \frac{x_{mit}}{\epsilon_{mit}} + \sum_k \rho'_{mk} \frac{W_{k^{a_{it}}}}{\epsilon_{mit}} + \phi'_m \frac{irri_{mit}}{\epsilon_{mit}} + \lambda'_m \frac{T_t}{\epsilon_{mit}} + \gamma'_m \frac{mills_{mit}}{\epsilon_{mit}} + \zeta_{mi} + \xi_{mit} \quad \dots \text{for all } m$$

m - crop and includes corn, soybean and upland cotton.

z_{mit} - dependent variable, yield of crop m in county i in year t .

x_{mit} - adoption percentage of GE acreage planted of all GE trait type for crop m .

$W_{k^{a_{it}}}$ - current year growing season climate factors (k^a) in county i in year t , including a) degree-days 8°C - 29°C, b) degree-days 29°C, c) precipitation in millimeters and d) precipitation square.

$irri_{mit}$ - percentage of crop m 's harvested acre irrigated.

T_t - time trend.

$mills_{mit}$ - crop m specific inverse mills ratio estimated using a plant or not plant probit model.

- For crop mix land use share, we use a fractional multinomial logit model:

$$E(y_{jit}|x, W) = \frac{\exp(\sum_m \beta_m^j x_{mit} + \sum_k \theta_k^j W_{k^{a_{it}}} + \gamma^j T_t + \varphi^j \bar{z}_i)}{1 + \sum_j \exp(\sum_m \beta_m^j x_{mit} + \sum_k \theta_k^j W_{k^{a_{it}}} + \gamma^j T_t + \varphi^j \bar{z}_i)} \quad \dots \text{for all } j$$

j - land use type including corn, soybean, cotton, pasture and all-other-crop.

y_{jit} - land use share for land use j .

W_{kit} - climate variables, including $W_{k^{a_{it}}}$ and a five previous year moving average of all the climate variables.

\bar{z}_i - the correlated random effect.

We also estimated a version with interaction terms between GE adoption rate and climate variables for yield and yield variance, and a version with interaction terms between GE adoption rate and long-term climate variable for land use.

Data

- USDA, National Agricultural Statistics Service (NASS), *June Agricultural Survey* from 1974-2020 for GE adoption rate, crop harvested acre, crop yield data, irrigation data
- USDA NASS Census of Agriculture from 1974-2022 for cropland and pastureland, crop land use share is constructed as $\frac{\text{crop harvested acre}}{\text{cropland} + \text{pastureland}}$
- European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset for all historical climate data

Results

- Higher yields:** In aggregate GE adoption raised U.S. corn, soybean, and upland cotton yields by 21–36% at current adoption, reducing climate impacts.
- Lower risk:** Nationwide each +1 pp in GE adoption cuts yield variance by 0.1–0.4%; current adoption implies 10–40% total variance reduction.
- Reduced northward shift:** GE adoption moderates northward displacement of corn and soybean by sustaining yields in warmer southern areas.

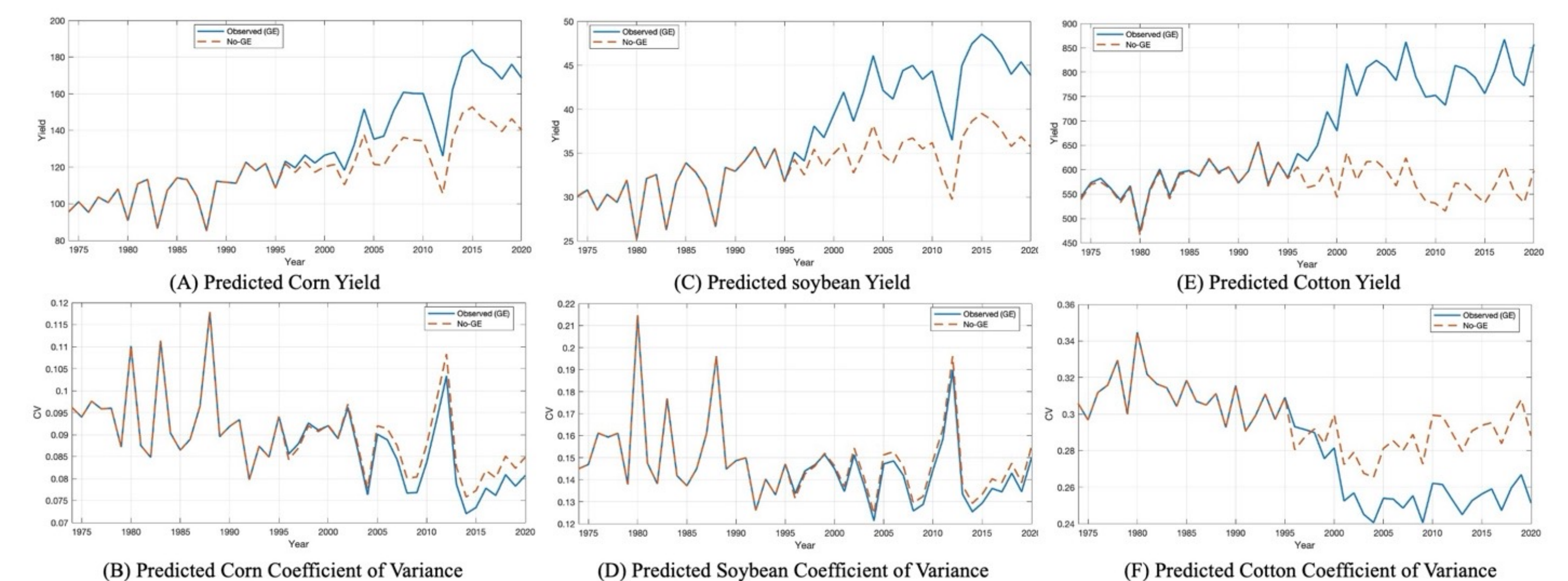


Figure 2. Prediction of the mean and coefficient of variance for US National Yields by Crop over the historical period 1974 to 2020

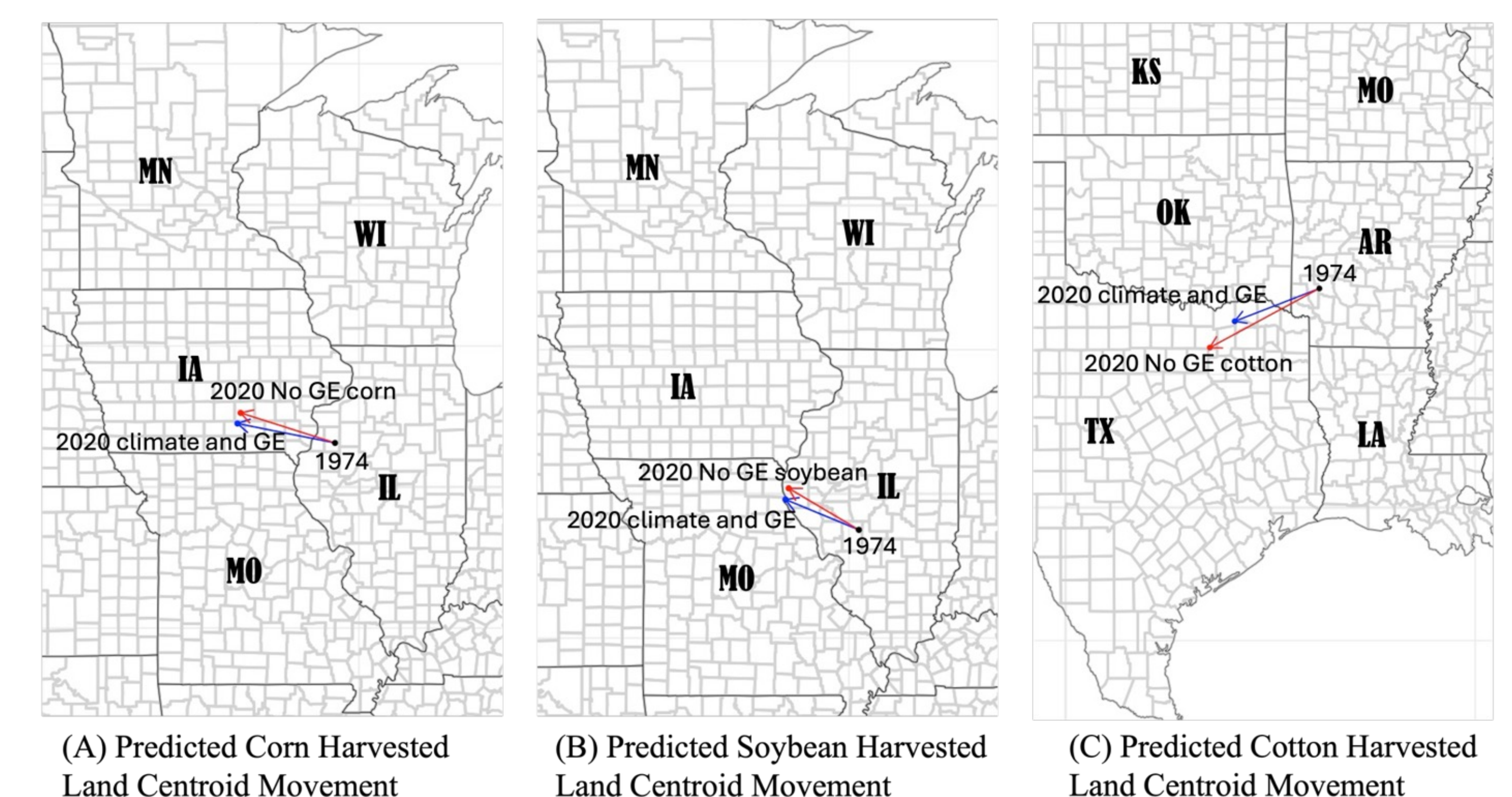


Figure 3. Prediction of US National Harvested Land Centroid Movement by Crop over the historical period 1974 to 2020

Discussion and Conclusions

GE varieties are climate adaptation tools. For corn, soybean, and upland cotton, GE raises mean yields, cuts yield variance and reduces sensitivity to extreme heat and problematic rainfall. GE adoption also moderates climate-driven spatial shifts, helping keep production in place.

Gains are bounded: protection weakens at very high temperatures, so next-gen stacked traits and complementary practices (planting windows, soil moisture, sustainable irrigation) are needed. GE movement moderation likely lowers infrastructure and logistics disruption and eases pressure on marginal lands. May want to pair added GE trait R&D with insurance and climate-smart ag to lower risk.

Nationally GE lowers climate yield shocks and shifts in production geography, but we don't model prices, policy shocks, water limits, or compound extremes, nor quantify downstream land, biodiversity, or groundwater effects. Would be desirable to: (i) stress-test GE-climate responses under warming to locate adaptation limits; (ii) study system-level implications for infrastructure, habitat, and water supply/demand. Bottom line: GE has reduced climate risk and slowed spatial change helping keep U.S. agriculture resilient.