A Productivity Indicator for Adaptation to Climate Change

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Abstract

This study draws on economic index theory to construct a new indicator for adaptation to changing environmental conditions, most notably climate change, which may shift the production technology over time. Such environmental shifts are largely exogenous to firm decision making, for instance investments in research and development, which may also lead to technology change. Few existing measures of total factor productivity (TFP) make this distinction, between exogenous environmental shifts and shifts

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due to firm decision making or innovation. We introduce a nonparametric Luenberger productivity indicator for adaptation, which allows for decomposition of standard technology and efficiency change measures into both environmental and production components. We apply this framework to agricultural production in the US Mississippi River Basin for recent decades, working with USDA Census of Agriculture data at the county level and key climate conditions. We also match the production and climate data to estimates of Nitrogen loading over time, to incorporate water quality into the adaptation indicator. Our results indicate sustained overall productivity growth, for both agricultural production and nitrogen loading reductions, driven by technology gains outweighing efficiency losses. Decomposing further to the adaptation components, our results indicate modest overall adaptation gains, driven by both adaptation efficiency and technology gains.

1 Introduction

Adaptation of agricultural production to changing environmental conditions entails some form of adjustment, either to take advantage of new opportunities or lessen harmful impacts (Burke and Lobell, 2010; National Resource Council, 2010; Zilberman et al., 2012; Burke and Emerick, 2016). To examine the role of adaptation for agricultural productivity, we employ economic index theory to construct a new productivity indicator for adaptation to changing environmental conditions, most notably climate change, which may shift the production technology over time, as well as lead to changes in efficiency relative to the new technology. Such environmental shifts are largely exogenous to firm decision making, for instance investments in research and development, which may also lead to technology change, while changes to efficiency are often more directly linked to production practices.

Our adaptation indicator draws on several recent total factor productivity (TFP) decompositions to consider environmental change. These include O'Donnell (2016), who adjusts measures of efficiency change for exogenous environmental change, as well as Chambers and

Pieralli (2020) and Chambers et al. (2020), who introduce a weather index change component to agricultural TFP. Our decomposition uses the Luenberger productivity indicator (Luenberger, 1995; Chambers et al., 1996; 1998; Chambers, 2002) to distinguish adaptation efficiency and technology change components to overall productivity.

We also extend the framework to integrate a biophysical model of nitrogen loading over time, which can be exacerbated by changing climate conditions (Sinha et al., 2017; Ballard et al., 2019). To our knowledge, we are the first to model climate adaptation both in terms of productivity and associated environmental condition.

We apply the adaptation indicator framework to agricultural production in the U.S. Mississippi River Basin, spanning the years 1987-2012. Our results indicate sustained overall productivity growth, for both agricultural production and nitrogen loading reductions, driven by technology gains outweighing efficiency losses. Decomposing further to the adaptation components, our results indicate modest overall adaptation gains, driven by both adaptation efficiency and adaptation technology gains.

2 Climate and agricultural productivity

2.1 The impact of climate change on agriculture

Perhaps more so than any other economic sector, agriculture and climate are intimately linked. Much of the literature in recent years on climate change and productivity focuses on the agricultural sector, with growing emphasis on adaptation, as well as some debate surrounding the extent of the effect for overall yields (Auffhammer et al., 2006; Deschênes and Greenstone, 2007; Timmins, 2006). Early evidence suggests overall negative effects of climate change for US agriculture, with minimal mitigation of these effects due to adaptation (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Wang et al., 2017). A lack of adaptation may be due to limited opportunities available to farmers, or to options that are only economically feasible over some range of the production technology (Burke and

Emerick, 2016), as well as uncertainty and risk management (Kim and Chavas, 2003; Falco and Veronesi, 2014; Yang and Shumway, 2016).

Wang et al. (2017) provide perhaps the most comprehensive analysis of long term climate effects on US agricultural productivity, covering the entire sector for the continental US states. Using stochastic frontier analysis (SFA) methods, they find that effects vary largely by region, with average losses to production efficiency due both to increasing aridity and heat stress. They also construct future projections based on their results, finding future efficiency losses most concentrated in the Mississippi Delta, greater Southeast, Corn Belt, and Plains regions.

2.2 Climate-adjusted measures of agricultural TFP

Few existing measures of total factor productivity (TFP) distinguish exogenous environmental shifts from shifts due to firm decision making or innovation[1]. O'Donnell (2016) introduces a new TFP decomposition which includes an *Environmental Efficiency* (EE) component, relating the production technology for a given set of environmental conditions to an encompassing metatechnology for all environmental conditions. Njuki et al. (2018; 2020) build on this in the context of climate change, by further distinguishing short term weather variation from longer term climate trends. Njuki et al. (2018) introduce separate environmental scale/mix efficiency and technical efficiency index decompositions, to distinguish exogenous shifts of the technology from managerial inefficiency. Njuki et al. (2020) introduce an explicit adaptation component to the TFP decomposition, to estimate the effect of long term climate trends on production. Each of the above employ parametric SFA methods for estimation of the associated distance functions in the first case, and production function in the latter.

Chambers and Pieralli (2020), and the related Chambers et al. (2020) introduce the first nonparametric decomposition of TFP to include a weather index component, and associated weather change indicator. Also similar to the SFA framework of Njuki et al. (2018;

[1] Refer to Shumway et al. (2016) for a review of US Department of Agriculture Economic Research Service (USDA ERS) methods for calculating agricultural productivity.

2020), Chambers and Pieralli (2020) and Chambers et al. (2020) include weather conditions as exogenous inputs to estimate the production frontier. They then interpret conventional measures of efficiency change relative to the production frontier as measures of adaptation to changing weather conditions. Results from Chambers at al. (2020) suggest that the decline in agricultural productivity growth for Australia (Alston et al., 2015; Sheng et al., 2010) is due to struggling climate-related adaptation to technological advances, rather than a slowdown in technological innovation. For US agriculture, Chambers and Pieralli (2020) find that adaptation to the frontier and technical change significantly impact the average state TFP.

2.3 Incorporating environmental effects into agricultural TFP

We take a production theoretical approach to model nitrogen pollution as part of the agricultural production technology. This draws on more general methods for incorporating undesirable outputs, along with intended output, into measures of efficiency and productivity. See Dakpo et al. (2016), Ancev et al. (2017), and Bostian et al. (2018) for recent reviews of this literature, as well as Bostian and Lundgren (2020) for a review of environmental adjustments to agricultural TFP specifically.

In one of the first analyses of nitrogen loading and agricultural TFP, Ball et al. (1994) find that at the time, agricultural TFP measures for US agriculture should be adjusted downward by 12-28 percent, due to environmental effects of nitrogen use. At the micro-level, Reinhardt et al. (1999) distinguish environmental efficiency (including excess nitrogen) from standard output technical efficiency for a sample of dutch dairy farms. A number of studies adopt a materials balance accounting approach to model nitrogen use and excess pollution for larger scale production (Hoang and Alauddin, 2010; Hoang and Coelli, 2011; Hoang and Wilson, 2017), generally finding potential for increases to agricultural production while also reducing nitrogen use.

A key insight from the broader literature on agricultural nitrogen pollution concerns the importance of spatial relationships, both for productivity and for runoff and loading in surrounding watershed systems (Helfand and House, 1995; Weinberg and Kling, 1996; Schwabe, 2001). Advances in computational optimization methods and integrated modeling for agriculture have made possible large scale modeling of these spatial relationships, linking economic production to environmental systems (Feng et al., 2006; Kling et al., 2014; Rabotyagov et al., 2014; Bostian et al., 2015; Whittaker et al., 2017; Barnhart et al., 2016; 2021; Xu et al., 2022). See also Plantinga (2015) for a review of the integrated modeling literature. Better understanding of these spatial relationships can facilitate spatial targeting of conservation policies for improved efficiency (Bostian et al., 2015; Whitaker et al., 2017) and individual management practices (Feng et al., 2006; Rabotyagov, 2014; Barnhart et al., 2021).

3 Methodology

3.1 The production technology

Our indicator relies on the underlying production technology, which we define for a vector of inputs $x = (x_1, ..., x_N)$ and a vector of outputs $y = (y_1, ..., y_M)$ as

$$T = \{(x, y) : x \,\text{can produce}\, y\} . \tag{1}$$

As defined, the technology in (1) tells us how inputs can be used to produce output, without accounting for environmental factors. O'Donnell (2016) likens this to a set of basic instructions or recipe, which can be counted upon under control conditions, and is generally neither lost nor forgotten over time. As a result, at any given point in time, there is some cumulative knowledge for how to use x to produce y. Following O'Donnell (2016), we define a second metatechnology to represent this accumulation of knowledge at time t as

$$T^t = \left\{(x^t, y^t) : x^t \,\text{can produce}\, y^t \,\text{in time}\, t\right\}, \tag{2}$$

where T^t encompasses the technologies of all preceding periods. In other words, what was possible yesterday is still possible today, so there can be no technical regress. We refer to this as the time t metafrontier.

But, just as changes in altitude may call for modifying a bread recipe, changes in environmental conditions may shift the production technology and require some form of adaptation by the firm.

We let $w = (w_1, ..., w_L)$ represent the set of relevant exogenous environmental conditions, and define a second environmental production metatechnology subject to these conditions as

$$T^t(w^t) = \left\{(x^t, y^t; w^t) : x^t \text{ can produce } y^t \text{ under conditions } w^t \text{ in time } t\right\}, \tag{3}$$

where the conditions in w^t remain outside the firm's control. We refer to this as the environmental metafrontier for time t. Production possibilities for given environmental conditions remain over time, while both changing environmental conditions and technical advance may expand this frontier over time.

We note this also draws on the earlier work of Ray (2004), who introduces environmental factors to the production technology, for both desirable and undesirable factors.

To also model undesirable outputs, such as pollution, we let $u = (u_1, ..., u_J)$ represent the set of undesirable output resulting from the production technology. Taking an output orientation of the production technology for both goods and bads yields the corresponding output sets, $P^t(x^t)$ and $P^t(x^t; w^t)$,

$$P^t(x^t) = \left\{(y^t, u^t) : x^t \text{ can produce } y^t \text{ and } u^t \text{ in time } t\right\}, \tag{4}$$

$$P^t(x^t; w^t) = \left\{(y^t, u^t) : x^t \text{ can produce } y^t \text{ and } u^t, \text{ given } w^t \text{ in time } t\right\}. \tag{5}$$

3.2 Optimal Production

Distance functions can be used to represent the technology for multi-input and multi-output production processes, either radially (Shephard, 1953; 1970) or by using the additive directional distance function (Chambers et al., 1996; 1998). Färe et al. (2003) show that the Shephard distance function can be recovered as a special case of the directional distance function. We use the more general directional distance function here, defined for the output orientations in (4) and (5) as

$$\vec{D}_O^t(x^t, y^t, u^t; g_y, g_u) = \max \{\beta : (y^t + \beta g_y, u^t - \beta g_u) \in P^t(x^t)\}, \tag{6}$$

$$\vec{D}_O^t(x^t, y^t, u^t; w^t, g_y, g_u) = \max \{\beta : (y^t + \beta g_y, u^t - \beta g_u) \in P^t(x^t; w^t)\}, \tag{7}$$

where the vector $\vec{g} = (g_y, g_u)$ specifies the direction of desirable output expansion and undesirable output contraction. Note, setting the direction vector $\vec{g}$ equal to observed output values specifies a radial expansion and contraction of goods and bads, while choosing the unit directional vector $(g_y, -g_u) = (1, -1)$ facilitates aggregation across technologies (Färe and Grosskopf, 2003). Given our interest in changing technologies over time, as well as adjusting for changing climate conditions, we employ the unit directional vector for this analysis. It is also possible to endogenize $\vec{g}$ for both nonparametric (Färe et al., 2013b; Hampf and Kruger, 2015; Daraio and Simar, 2016) and parametric models (Färe et al., 2017; Atkinson and Tsionas, 2018).

The directional distance function satisfies a number of key axiomatic properties from production theory.[2] For a given technology, these include:

i. Translation property.
$\vec{D}_O(x, y + \alpha g_y, u - \alpha g_u; g_y, g_u) = \vec{D}_O(x, y, u; g_x, g_y) - \alpha,\ \alpha \in \Re$

ii. Homogeneity of degree -1 in $\vec{g}$.
$\vec{D}_O(x, y, u; \lambda g_y, \lambda g_u) = \lambda^{-1}\vec{D}_O(x, y, u; g_y, g_u),\ \lambda > 0$

iii. Representation property.
$\vec{D}_O(x, y, u; g_y, g_u) \geq 0$ if and only if $(y, u) \in P(x)$

[2]See Färe et al. (2003) for more complete review and associated proofs.

iv. Monotonicity of outputs.

$\vec{D}_O(x, y', u; g_y, g_u) \leq \vec{D}_O(x, y, u; g_y, g_u)$, $y' \geq y$, for freely disposable y

$\vec{D}_O(x, y, u'; g_y, g_u) \leq \vec{D}_O(x, y, u; g_y, g_u)$, $u' \leq u$, for weakly disposable u

v. Homogeneity of degree +1 in outputs.

$\vec{D}_O(x, \lambda y, \lambda u; g_y, g_u) = \lambda \vec{D}_O(x, y, u; g_y, g_u)$, $\lambda > 0$, for constant returns to scale (CRS)

Given these properties, the directional distance function provides a complete representation of the production technology. The resulting distance value provides a measure of inefficiency in the direction (g_y, g_u), where $\vec{D}_O(x, y, u; g_y, g_u) = 0$ for efficient firms operating on the frontier and $\vec{D}_O(x, y, u; g_y, g_u) > 0$ for inefficient firms operating below the frontier, increasing in value with inefficiency.

We estimate the technology models defined in (2) and (3), and corresponding directional distance functions defined in (6) and (7), nonparametrically, using Activity Analysis or Data Envelopment Analysis (DEA) methods. Beginning with the metatechnology output set, $P^t(x^t)$, we solve for each observation $k = 1, \ldots, K$, in each time period $(t, \tau) = 1, \ldots, T$,

$$\begin{aligned}
\vec{D}_O(x, y, u; g_y, g_u) = \max \{\beta : & \\
y_m^t + \beta \leq & \sum_{\tau=1}^{t}\sum_{k=1}^{K} z^{\tau k} y_m^{\tau k}, m = 1, \ldots, M, \\
u_n^t - \beta = & \sum_{\tau=1}^{t}\sum_{k=1}^{K} z^{\tau k} u_j^{\tau k}, j = 1, \ldots, J, \tau = 1, \ldots, t, \\
x_n^t \geq & \sum_{\tau=1}^{t}\sum_{k=1}^{K} z^{\tau k} x_n^{\tau k}, n = 1, \ldots, N, \tau = 1, \ldots, t, \\
\sum_{\tau=1}^{t}\sum_{k=1}^{K} z^{\tau k} \leq & 1, \tau = 1, \ldots, t, \\
z^{\tau k} \geq & 0,\ k = 1, \ldots, K, \tau = 1, \ldots, t\},
\end{aligned} \tag{8}$$

where $z^\tau = z^{\tau 1}, ..., z^{\tau K}$, also known as intensity variables, are used to construct the cumulative output set metafrontier as the convex combination of the outermost output values in each time period, t. The constraints for y_m^t and x_n^t allow for strong or free disposability of desirable outputs and inputs, while the u_j^t constraints impose weak disposability for undesirable outputs. To include environmental conditions (namely, climate), we add to (8) the environmental constraint, $w_l^t = \sum_{\tau=1}^{t}\sum_{k=1}^{K} z^{\tau k} w_l^{\tau k}, l = 1, \ldots, L, \tau = 1, \ldots, t$, which also imposes weak disposability for environmental conditions.

Figure 1 illustrates the production metatechnology conceptually, for time periods t, and $t+1$, focusing for simplicity on desirable output only. In this example, both technologies expand from t to $t+1$, though by different amounts. The ray extending from observation k to the T^t frontier represents the directional technology distance in the g direction (here contracting inputs, and expanding outputs) where the corresponding point k^{t*} on the frontier represents efficient production in time t. A similar interpretation holds for the ray extending from k to the environmental frontier, where the corresponding point k_w^{t*} represents efficient production in time t, under environmental conditions w. The dashed ray from k^{t*} to k_w^{t*} represents the change in the production technology due to environmental conditions at time t, or alternatively, the difference in distance to the frontiers, with and without changing environmental conditions.

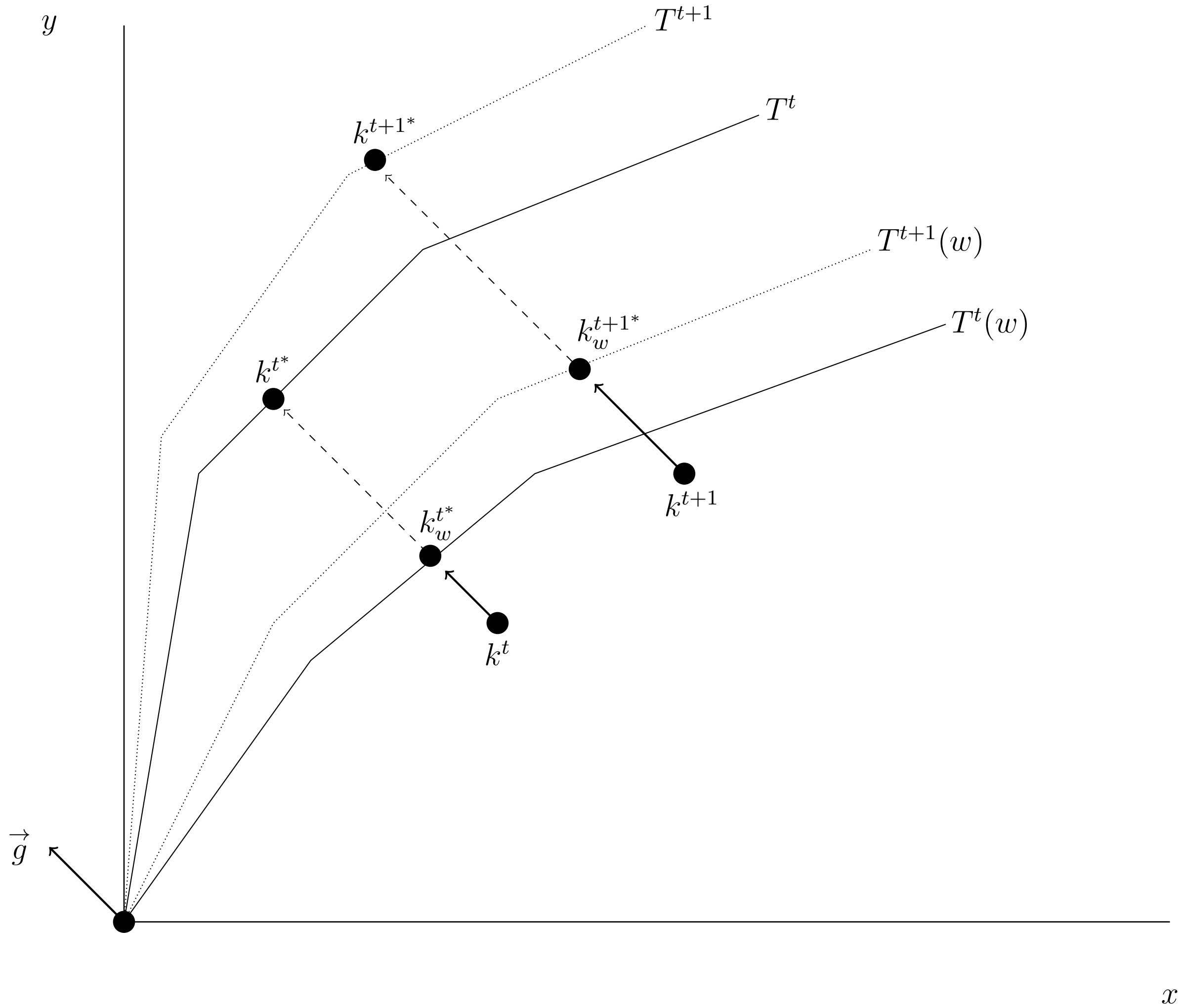


Figure 1: The directional output distance function and production metatechnology subject to environmental conditions w, for observation k in time periods $(t, t+1)$, with technical progress.

3.3 The Luenberger adaptation indicator

Adaptation to changing environmental conditions depends on the change in the cumulative metatechnology, the extent of environmental change and the change in efficiency relative to the new environment. We use the Luenberger productivity indicator to identify these adaptation components to overall productivity from one time period to the next. We begin with the Luenberger productivity indicator (maintaining the output orientation), $LUEN(t, t+1)$, for time periods $(t, t+1)$,

$$\begin{aligned} LUEN(t,t+1) =& \frac{1}{2}\left[\vec{D}_O^{t+1}(x^t, y^t, u^t; g_y, g_u) - \vec{D}_O^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; g_y, g_u)\right] \\ &+ \frac{1}{2}\left[\vec{D}_O^{t}(x^t, y^t, u^t; g_y, g_u) - \vec{D}_O^{t}(x^{t+1}, y^{t+1}, u^{t+1}; g_y, g_u)\right], \end{aligned} \tag{9}$$

which can be decomposed (Chambers et al., 1996) into separate measures of efficiency change,

$$LECH(t,t+1) = \vec{D}_O^{t}(x^t, y^t, u^t; g_y, g_u) - \vec{D}_O^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; g_y, g_u), \tag{10}$$

and technology change,

$$\begin{aligned} LTCH(t,t+1) =& \frac{1}{2}\left[\vec{D}_O^{t+1}(x^{t+1}, y^{t+1}, u^{t+1}; g_y, g_u) - \vec{D}_O^{t}(x^{t+1}, y^{t+1}, u^{t+1}; g_y, g_u)\right] \\ &+ \frac{1}{2}\left[\vec{D}_O^{t+1}(x^t, y^t, u^t; g_y, g_u) - \vec{D}_O^{t}(x^t, y^t, u^t; g_y, g_u)\right], \end{aligned} \tag{11}$$

where overall productivity $LUEN(t,t+1) = LECH(t,t+1) + LTCH(t,t+1)$. Färe and Zelenyuk (2019) provide recent theoretical justification for weighting the indicator equally across time periods, in order to satisfy the time reversal property for aggregation. We let $LUEN_{(w)}$ denote the environmental technology analogues to (9) - (11).

Our adaptation indicator considers changes in efficiency, relative to the environmental frontier, as well as changes to the environmental technology, relative to changes in the cumulative metatechnology. We use the Luenberger framework above to define the adaptation indicator, which we denote $AI(t, t+1)$, as

$$AI(t, t+1) = LUEN_{(w)}(t, t+1) - LUEN(t, t+1), \tag{12}$$

with the corresponding efficiency and technology change components,

$$AIEC(t, t+1) = LECH(w)(t, t+1) - LECH(t, t+1), \tag{13}$$

$$AITC(t, t+1) = LTCH(w)(t, t+1) - LTCH(t, t+1), \tag{14}$$

Intuitively, the indicator measures adaptation as the difference in productivity, with and without including environmental conditions in the production technology. As productivity is itself a measure of change in output to change in input over time, this lends a difference in differences interpretation to the adaptation indicator. In Figure 1, observation k loses efficiency over time, relative to both technologies, $T^{t,t+1}, T^{t,t+1}(w)$. However, the loss of efficiency to the environmental frontier is smaller, implying a positive adaptation efficiency change component, $AIEC > 0$. Likewise, while both technologies expand, the environmental technology expands by less, implying a negative adaptation technology change component, $AITC < 0$. The sign of the overall adaptation productivity indicator, AI, would depend on the relative magnitudes of the adaptation efficiency gain and technology loss.

3.4 A long differences approach to climate trends

To consider adaptation over longer time horizons associated with climate change, we follow the recent long differences approach of Burke and Emerick (2016) to distinguish longer term climate trends from annual weather variation. Let $\Theta = (\Theta_{S_1}, ..., \Theta_{S_P})$ represent a vector of P successive climate time periods, each of length S_p, $p = 1, ..., P$. We use $\bar{x}^{\Theta_{S_p}}$, $\bar{y}^{\Theta_{S_p}}$, $\bar{u}^{\Theta_{S_p}}$, and $\bar{w}^{\Theta_S}$, to represent the climate period average values for the production variables. We then estimate both the metatechnology and environmental metatechnology for each climate period, using these period average values, in order to model longer term change. This yields the climate period technologies, $T^{\Theta_{S_p}}$ and $T^{\Theta_{S_p}}(\bar{w}^{\Theta_{S_p}})$, defined as in (1) and (3), as well as corresponding output sets, $P^{\Theta_{S_p}}(\bar{x}^{\Theta_{S_p}})$ and $P^{\Theta_{S_p}}(\bar{x}^{\Theta_{S_p}}; \bar{w}^{\Theta_{S_p}})$, defined as in (4) and (5). Note that the technology for each climate period represents the cumulative metatechnology, including all preceding climate periods.

For our analysis, we construct three 5-year climate periods (i.e., $P = 3$ and $S_p = 5, p = 1, 2, 3$) based on USDA Census of Agriculture years: 1987-1992, 1997-2002, and 2007-2012. We refer to these as the 1990, 2000, and 2010 climate periods. We employ the Luenberger framework for productivity and adaptation outlined in (9)-(12) to measure change between climate periods.

4 Application to US Mississippi River Basin (EMRB)

4.1 Data construction

We apply the productivity indicator framework to agricultural production and nitrogen loading in the US Mississippi River Basin, one of the most productive regions for agriculture globally. Nitrogen runoff from agricultural production in the basin also remains a leading contributor to in-stream eutrophication and annual hypoxia in the Gulf of Mexico, commonly known as the “Dead Zone” (Kling, 2014; US EPA, 2017). This makes the region particularly relevant for analysis of management practices and policy design to reduce nitrogen runoff and subsequent loading in the basin (Rabotyagov et al., 2010; 2014; Kurkalova, 2015; Barnhart et al., 2016;2021; Kling et al., 2017; Ancev et al., 2021).

Following Burke and Emerick (2016), we limit our analysis to areas east of the 100th Meridian, to mitigate the role of irrigation in production. We refer to this as the Eastern Mississippi River Basin (EMRB). We extend the Burke and Emerick (2016) production data, originally drawn from Schlenker and Roberts (2009), to now include USDA Census of Agriculture years 1978 - 2012. Our analysis considers the subset years, 1987-2012.[3] The production data include county-level aggregate values for agricultural sales and expenditures. We use the USDA national PPI and CPI to convert all monetary values to 1990-1992 base year values. Table 1 summarizes the production data.

We use GIS to aerially prorate the county-level production data to 4 km grid resolution climate data, drawn from the PRISM Climate Group, and to subbasin-level estimates for nitrogen loading, drawn from Sinha et al. (2017).[4] This data construction follows related work to match subbasin-level nitrogen loading to agricultural production data (Bostian et al., 2015), as well as in the study region (Barnhart et al., 2016; Ancev et al., 2021). Figure 2 presents the spatial distribution for temperature and precipitation in the EMRB for the 1990-2010 study climate periods, while Figure 3 presents similar spatial distributions for the production variables and nitrogen loading.[5]

Looking at these spatial distributions, we see increases to precipitation over much of the middle regions of the basin, with northern and southern-most regions becoming drier for growing season months. We also see varying levels of temperature increase over most of the basin, with more extreme increases in the northern-most regions. The expenditure ratio generally improved for most of the basin, and most so in the upper midwest regions, areas where nitrogen loading levels also became more concentrated.

The PRISM climate data include monthly values for temperature, dew point and precipitation. Rather than include these weather variables directly in the technology model, we follow Wang et al. (2017) to construct two separate weather indexes: The Oury (1965) aridity index for crop production and a temperature-humidity index (THI) to measure heat-stress conditions for livestock production.

[3]We restrict to this subset to overlap available nitrogen loading estimates from Sinha et al. (2017).

[4]PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu

[5]Note, all climate data are reported in terms of 30-year climate normals, computed as the average value from the preceding 30 years.

The Oury index for time t is constructed as:

$$\text{Oury} = \frac{\text{Precipitation}}{1.07^{\text{Temperature}}}, \tag{15}$$

where temperature is measured in degrees Celsius and precipitation in millimeters. The THI is constructed as:

$$\text{THI} = (\text{Dry Bulb Temperature}) + (0.36 * \text{Dew Point Temperature}) + 41.2, \tag{16}$$

where temperature is again measured in degrees Celsius. Following Wang et al. (2017), we restrict the Oury index to the growing season months, April-August and construct annual THI values. Table 1 presents summary statistics for the climate variables and index values. Note, as with the raw weather variables, all weather index values are reported in terms of 30-year climate normals.

We use this weather index approach to better satisfy the production technology axioms for monotonicity. Raw temperature and precipitation values often present thresholds, below which, more rain or warmer temperatures may be production-increasing, but above which, the opposite holds (Lobell and Asner, 2003). For instance, Schlenker and Roberts (2009) find that after gradual yield growth increases up to 29-32 degrees Celsius, corn, cotton, and soy experience rapid decreases in yield growth. By contrast, the Oury and THI values imply consistent production relationships over their range of possible values. For the Oury, higher values imply lower aridity, and more favorable conditions for crop production. The THI increases with heat stress, implying less favorable conditions for livestock production (Mukkerjee et al., 2012; Key and Sneeringer, 2014).[6]

To overview the data in Table 1, while land in agriculture remained relatively stable over the study period, both sales and expenditures increased in real terms. The 30-year climate

[6] Oury index values below 20 indicate drought conditions, while THI values greater than 70 indicate stress to cattle livestock (St. Pierre, et al., 2003; Wang et al., 2017).

normals for growing season temperature and precipitation increase on average, while the resulting Oury and THI index values remain relatively stable. Nitrogen loading increases, peaking during the 2000 climate period.

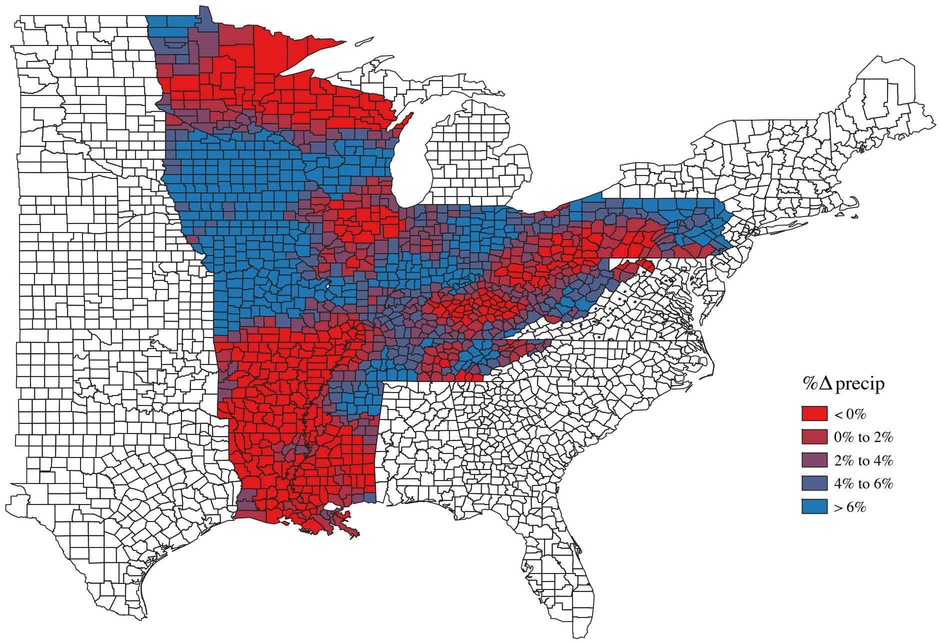
Table 1: Summary statistics for the EMRB study region, county-level climate period averages (1,214) counties).

Variable	Mean	Std. Dev.	Min	Max
1990 Climate Period				
Ag Land (acres)	189,510.2	125,644.4	0	1,075,711
Sales (1,000s)	48,145.37	48,941.51	0.00	694,762.30
Expenditures (1,000s)	37,185.06	37,622.76	0.00	521,989.80
Monthly Temp (C)	19.74	2.64	12.49	25.63
Monthly Precip (mm)	102.29	11.75	63.09	153.18
Monthly Oury	28.64	3.48	20.05	48.57
Monthly THI	54.86	4.88	42.56	67.20
Nitrogen Load (kg/km2)	377.45	306.78	10.08	2,832.91
2000 Climate Period				
Ag Land (acres)	188,804.6	125,943.5	0	1,111,199
Sales (1,000s)	55,686.67	58,527.55	0.00	814,638.80
Expenditures (1,000s)	40,071.73	41,438.19	8.85	581,816.80
Monthly Temp (C)	19.96	2.61	12.85	26.06
Monthly Precip (mm)	104.27	11.62	64.51	153.38
Monthly Oury	28.41	3.83	19.73	48.17
Monthly THI	55.01	4.89	42.73	67.37
Nitrogen Load (kg/km2)	523.93	457.54	10.05	7,704.54
2010 Climate Period				
Ag Land (acres)	189,767.5	123,811.6	324	1,086,947
Sales (1,000s)	65,029.61	73,453.81	2.09	844,548.20
Expenditures (1,000s)	42,482.98	46,368.19	5.92	578,636.80
Monthly Temp (C)	20.26	2.60	13.19	26.52
Monthly Precip (mm)	105.89	11.49	71.05	155.19
Monthly Oury	28.14	4.21	18.22	47.11
Monthly THI	55.33	4.83	43.18	67.59
Nitrogen Load (kg/km2)	404.75	374.25	9.07	3,291.96

Note, all sales and expenditure values are reported in 1990-1992 USD.

4.2 Inefficiency results

To consider inefficiency under different environmental conditions and production objectives, we estimate four versions of the directional distance model from (8). The first model considers



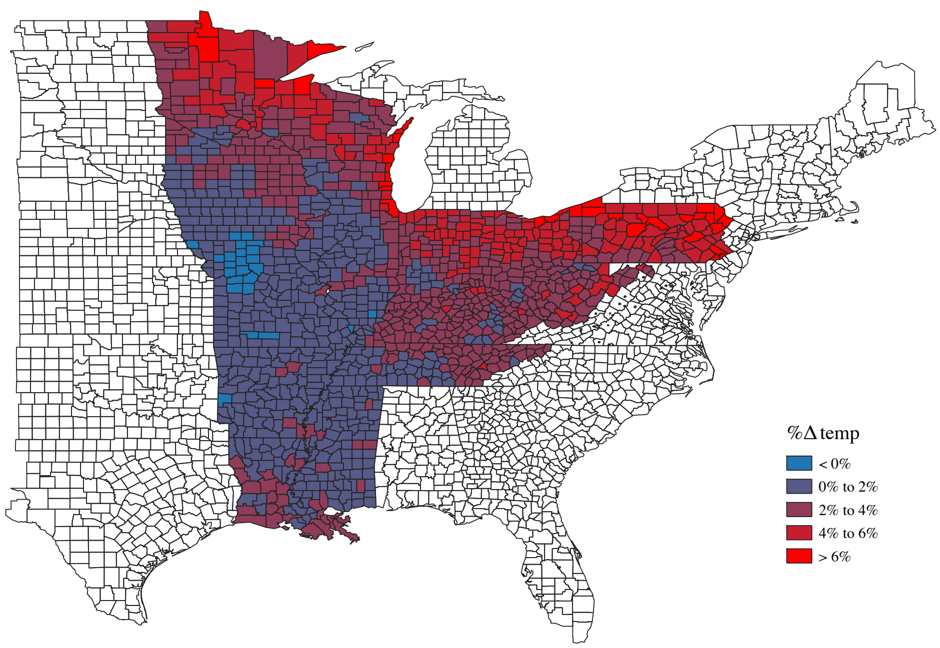
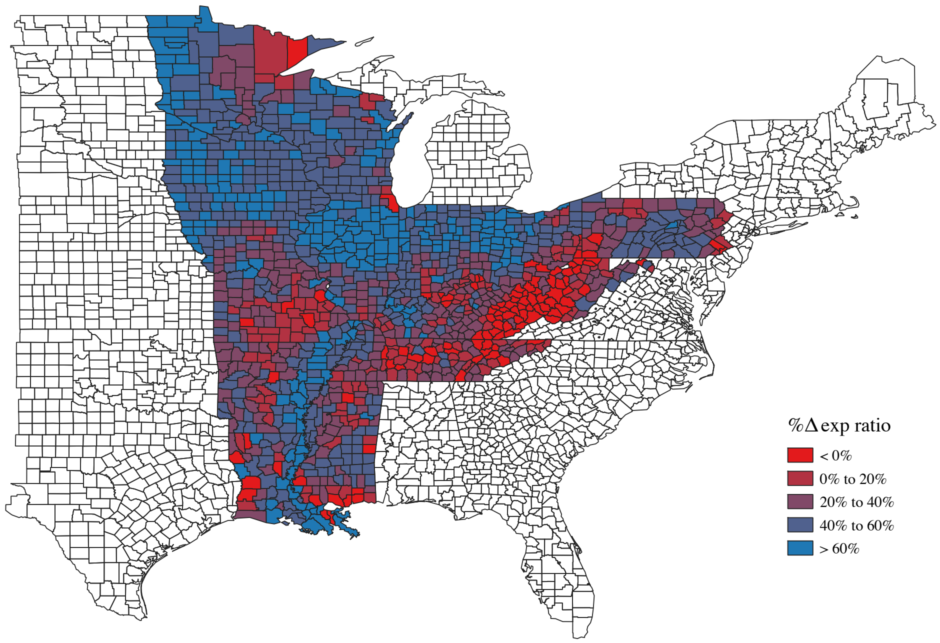


Figure 2: The percent change in mean growing season temperature and precipitation from 1990 to 2010



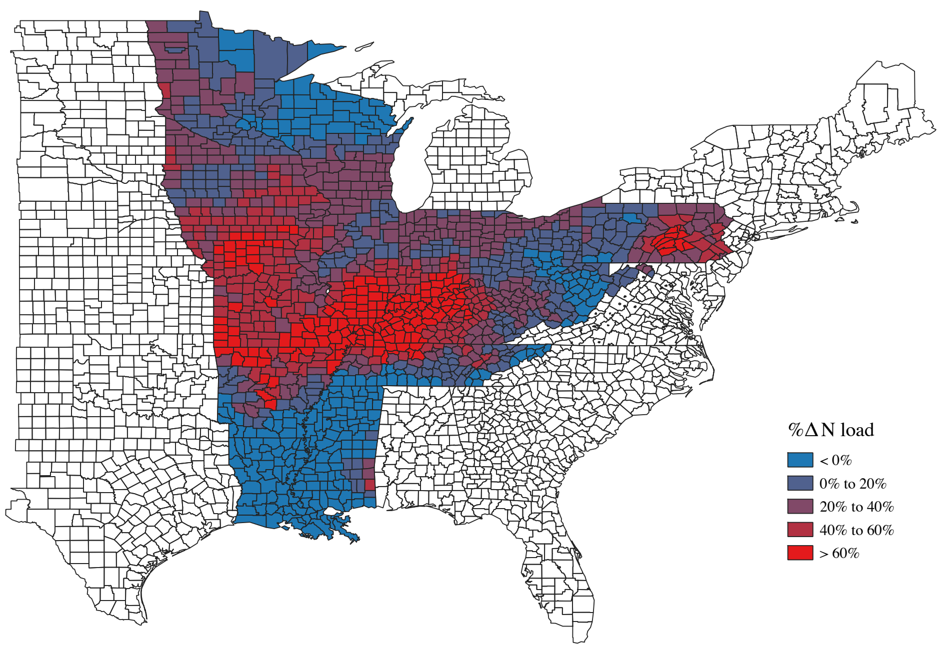


Figure 3: The percent change in the production expenditure ratio (Sales to Expenditures) and nitrogen loading from 1990 to 2010

only the agricultural production objectives, setting $(g_y, -g_u) = (1, 0)$, without including climate normals or nitrogen loading. The second model includes the climate normals, still setting $(g_y, -g_u) = (1, 0)$, while the third includes nitrogen loading, setting $(g_y, -g_u) = (1, -1)$, but omits the climate normals. The fourth model jointly maximizes production output and minimizes nitrogen loading, while also including the climate normals. In each case, the model considers time t observations, relative to the time t metatechnology frontier. Table 2 presents the corresponding model results.

Table 2: Inefficiency results for the EMRB study region, 1990 - 2010 (1,214) counties).

Variable	Mean	Std. Dev.	Min	Max
1990				
Distance	0.289	0.154	0.000	0.804
Distance (w)	0.231	0.150	0.000	0.686
Distance (N)	0.256	0.147	0.000	0.785
Distance (N;w)	0.200	0.143	0.000	0.686
2000				
Distance	0.378	0.184	0.000	1.250
Distance (w)	0.301	0.169	0.000	1.168
Distance (N)	0.319	0.173	0.000	1.084
Distance (N;w)	0.253	0.161	0.000	0.964
2010				
Distance	0.381	0.187	0.000	1.020
Distance (w)	0.310	0.176	0.000	0.949
Distance (N)	0.303	0.168	0.000	0.927
Distance (N;w)	0.255	0.165	0.000	0.887

Note, all data were mean-weighted for estimation purposes, so that values can be interpreted as % of sample mean. We use (w) and (N) to denote the inclusion of climate variables and nitrogen loading, respectively.

Average inefficiency values range from approximately 20 to 38 percent of mean production values, and generally increase over the study period. Lower inefficiency with the inclusion of climate normals implies an inward shift of the environmental frontier, relative to the production metatechnology, similar to the conceptual depiction in Figure 1. This pattern holds across climate periods, and both with and without adding the nitrogen loading objective. For the nitrogen loading models, we see the greatest inefficiency levels for the 2000 climate period, which corresponds to the concurrent peak in nitrogen loading for the basin. Including the nitrogen loading objective also generally lowers inefficiency estimates, implying less potential for increases to agricultural output when also working to reduce nitrogen loading.

4.3 Productivity and adaptation indicator results

As with the underlying inefficiency models, we construct four versions of the Luenberger productivity indicator, with and without the nitrogen objective and climate normals. We also consider shorter-term changes in productivity between climate periods (1990-2000, 2000-2010), as well as longer term productivity over the entire study period (1990-2010). Table 3 presents the corresponding model results.

Table 3: Luenberger indicator results for the EMRB study region, 1990 - 2010 (1,214) counties).

	Production Only				Production and N loading			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
1990-2000								
LECH	-0.090	0.088	-0.625	0.451	-0.063	0.080	-0.453	0.349
LTCH	0.153	0.100	0.000	1.084	0.117	0.091	0.000	0.980
LUEN	0.063	0.124	-0.321	1.084	0.054	0.113	-0.272	1.255
LECH (w)	-0.069	0.097	-0.619	0.450	-0.053	0.091	-0.454	0.461
LTCH (w)	0.145	0.099	0.000	1.424	0.128	0.116	0.000	1.365
LUEN (w)	0.075	0.131	-0.323	1.424	0.075	0.144	-0.259	1.476
2000-2010								
LECH	-0.003	0.129	-0.573	0.836	0.016	0.122	-0.567	0.687
LTCH	0.107	0.118	0.000	1.169	0.062	0.093	0.000	0.917
LUEN	0.104	0.185	-0.339	1.436	0.078	0.160	-0.316	1.157
LECH (w)	-0.010	0.129	-0.670	0.884	-0.002	0.121	-0.696	0.940
LTCH (w)	0.135	0.172	0.000	1.796	0.108	0.149	0.000	1.118
LUEN (w)	0.125	0.218	-0.333	1.977	0.106	0.192	-0.325	1.640
1990-2010								
LECH	-0.093	0.126	-0.605	0.598	-0.047	0.122	-0.552	0.581
LTCH	0.256	0.206	0.000	1.695	0.176	0.164	0.000	1.249
LUEN	0.164	0.249	-0.337	2.267	0.129	0.215	-0.272	1.772
LECH (w)	-0.079	0.141	-0.669	0.581	-0.055	0.133	-0.616	0.662
LTCH (w)	0.252	0.210	0.000	2.607	0.185	0.159	0.000	1.931
LUEN (w)	0.172	0.259	-0.305	3.090	0.130	0.204	-0.250	2.195

Note, all data were mean-weighted for estimation purposes, so that values can be interpreted as % of sample mean. We use (w) and (N) to denote the inclusion of climate variables and nitrogen loading, respectively.

To overview, we begin with the composite productivity indicator values. Across models, productivity increases over the study period, with average inter-climate period gains ranging from 5.4 to 12.5 percent, and greater gains for the 2000-2010 period. Average productivity estimates for the entire 1990-2010 period range from 12.9 to 17.2 percent. Using the decomposition, we can attribute overall productivity gains mainly to gains in the production technology, or an outward shift of the production frontier across time. Average technology gains range from 6.2 to 15.3 percent for the inter-climate period models, and from 17.6 to 25.6 percent for entire study period. Technology gains generally outweigh efficiency losses, which range on average from -0.3 to -9.0 percent for the inter-climate period models and from -0.47 to -9.3 percent for the entire study period. We do find modest average efficiency gains for the 2000-2010 nitrogen loading model, still outweighed by technology gains in that case. This general pattern of technology gains outweighing efficiency losses, resulting in overall productivity gains, is consistent with previous recent analyses of climate and US agricultural productivity (Nujuki et al., 2019; Chambers and Pieralli, 2020)

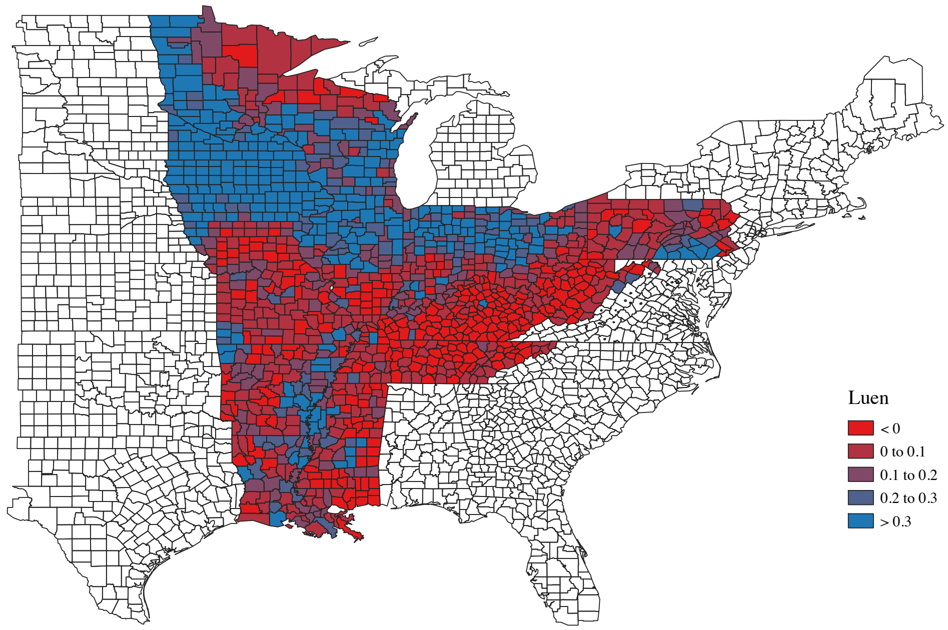
Comparing the nitrogen loading results to the production only results, we generally see smaller overall productivity gains when taking nitrogen into account. The same pattern of technology gains outweighing efficiency losses (or modest efficiency gains) holds.

Figures 4 and 5 present the spatial distributions for the productivity indicator results from each of the models. We see similar spatial patterns across models, with the highest productivity gains concentrated in the upper-Midwest region of the basin, and losses mainly in the South and eastern regions. For the nitrogen loading models, we see a similar pattern, but with more areas of productivity loss in the Midwest, where nitrogen loads became more concentrated over the study period.

The adaptation indicator takes the difference between the productivity indicator (and sub-component) values, with and without the change in climate normals. In Table 3, average productivity gains with climate normals included outweigh those without, to varying degrees. To better understand the underlying components to this difference, Table 4 presents the adaptation indicator and sub-component results.

The overall adaptation indicator values range from 1.2 to 2.8 percent for the inter-climate periods, versus 0.1 to 0.9 percent for the entire study period. For the 1990-2000 period, efficiency losses to the climate-adjusted frontier were less than those to the metatechnology frontier, indicating net adaptation efficiency gains. This pattern reverses for the 2000-2010 period, while for the 1990-2010 period as a whole, we find average net adaptation efficiency gains of 1.3% for the production only model, versus net adaptation efficiency losses of 0.8% for the nitrogen loading model. We find overall adaptation technology losses of -0.4% for the production only model over the entire period (i.e., the climate-adjusted metafrontier expanded by less than the production metafrontier), but average gains of 2.8% for the 2000-2010 period. Technology gains persist on average for the nitrogen loading model, with overall adaptation gains of 0.9% over the entire period. Adaptation technology gains indicate the climate-adjusted frontier expanded more, proportionately, than the production metatechnology frontier.

Figure 6 presents the spatial distribution of the adaptation indicator values. Compared to the previous productivity results, we find greater spatial dispersion of adaptation indicator values, for both the production-only and nitrogen loading models. Areas extending from the upper-Midwest to lower South exhibit adaptation gains above 2 percent, with additional positive gains over much of the eastern regions of the basin as well. Adaptation losses are more pronounced in the upper portions of the basin for the production-only model, while more dispersed over the center regions for the nitrogen loading model.



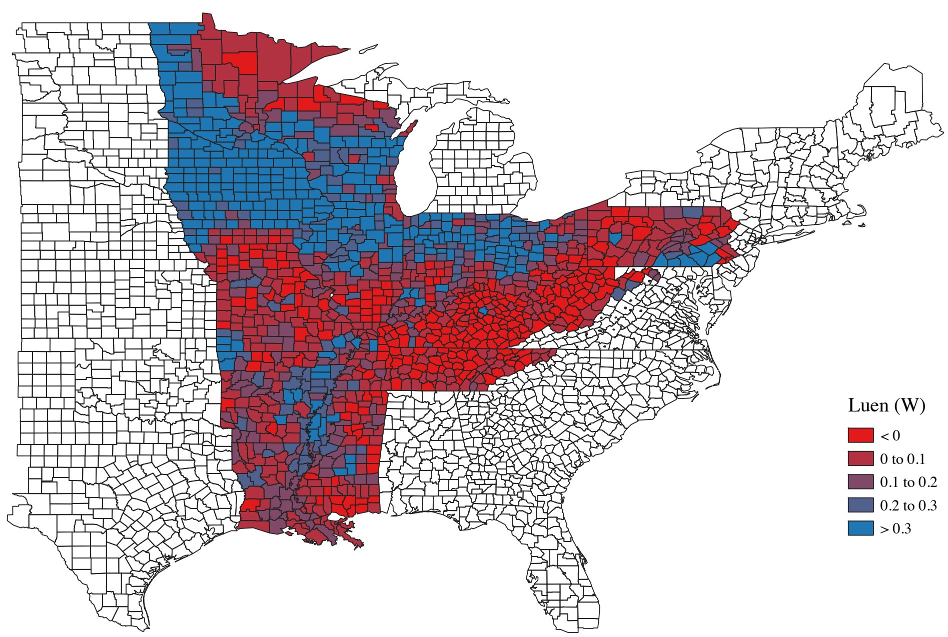
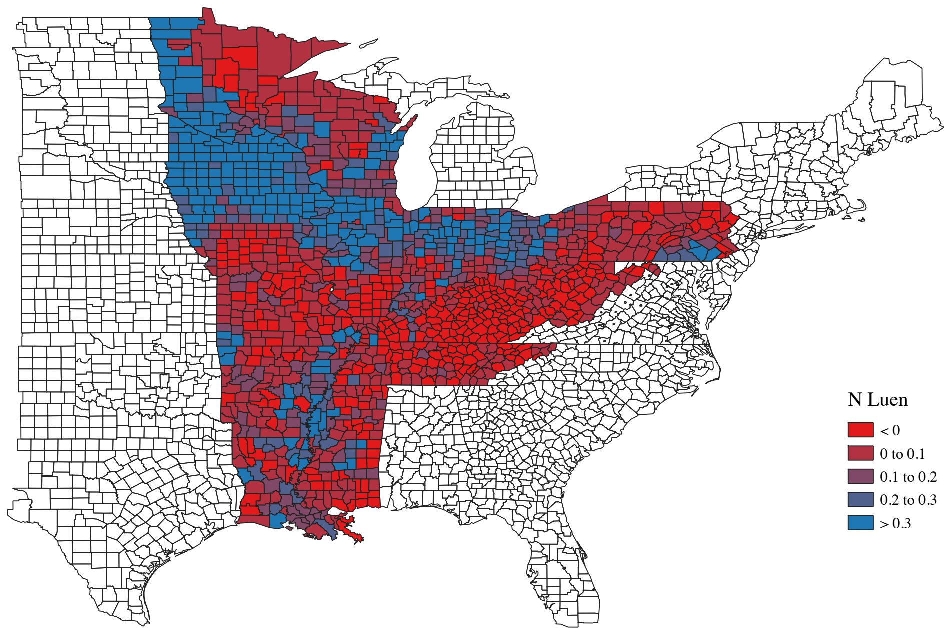


Figure 4: Luenberger productivity indicator results from 1990 to 2010, with and without including changing climate normals



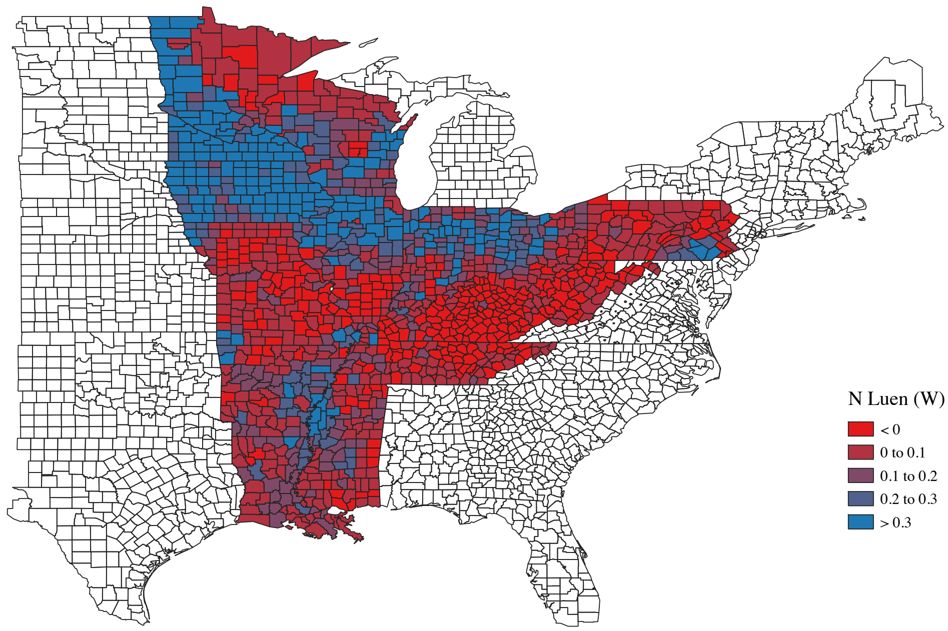
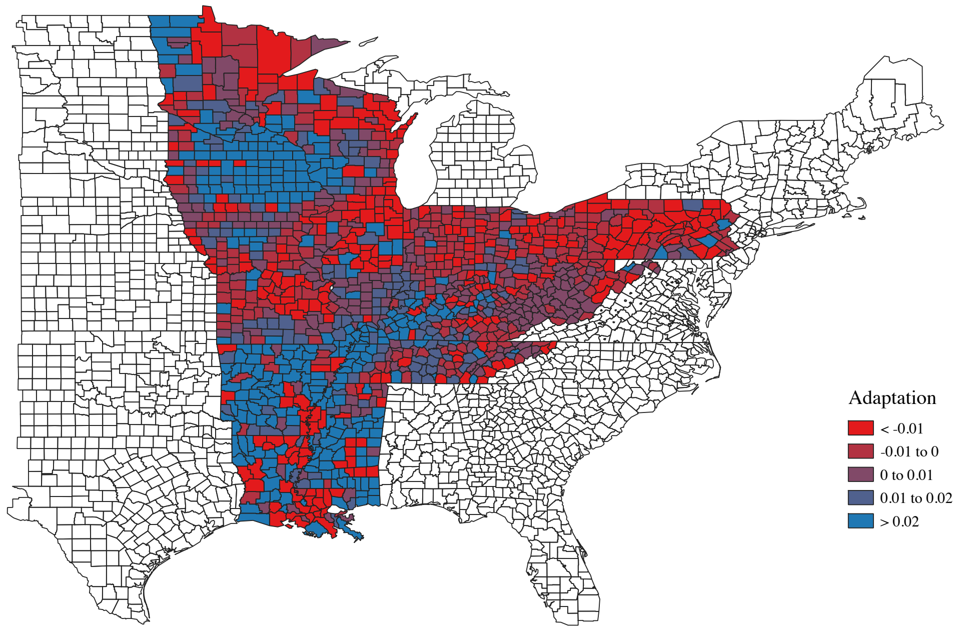


Figure 5: Luenberger productivity indicator results for nitrogen loading from 1990 to 2010, with and without including changing climate normals



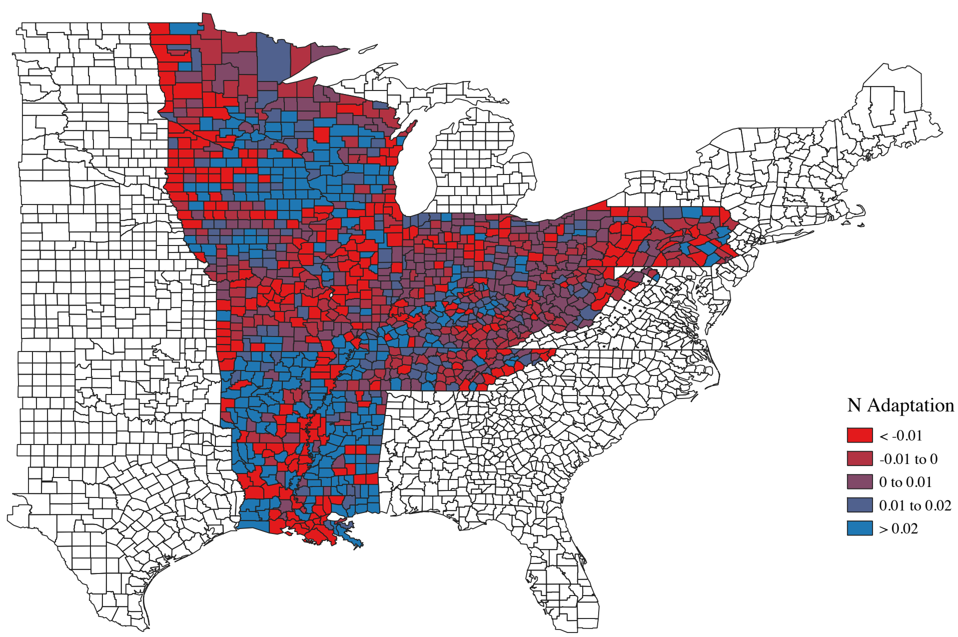


Figure 6: Adaptation indicator results from 1990 to 2010, with and without including Nitrogen loading

Table 4: Adaptation indicator results for the EMRB study region, 1990 - 2010 (1,214) counties).

	Production Only				Production and N loading			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
1990-2000								
AIEC	0.020	0.056	-0.142	0.334	0.009	0.055	-0.159	0.500
AITC	-0.009	0.059	-0.323	0.340	0.012	0.082	-0.238	1.263
AI	0.012	0.032	-0.132	0.340	0.021	0.076	-0.103	1.376
2000-2010								
AIEC	-0.007	0.037	-0.192	0.165	-0.018	0.050	-0.374	0.340
AITC	0.028	0.106	-0.084	1.388	0.045	0.103	-0.420	0.969
AI	0.021	0.099	-0.110	1.401	0.028	0.087	-0.420	0.905
1990-2010								
AIEC	0.013	0.059	-0.206	0.314	-0.008	0.056	-0.223	0.452
AITC	-0.004	0.071	-0.513	0.938	0.009	0.074	-0.719	0.682
AI	0.009	0.051	-0.365	0.823	0.001	0.065	-0.705	0.671

Note, all data were mean-weighted for estimation purposes, so that values can be interpreted as % of sample mean. We use (w) and (N) to denote the inclusion of climate variables and nitrogen loading, respectively.

5 Conclusion

Changing climate conditions highlight the importance of adaptation for sustained agricultural productivity growth. We contribute to recent efforts to measure the adaptation component to overall productivity by developing a Luenberger productivity indicator for adaptation. Our indicator measures adaptation as the difference in productivity, with and without including climate in the production technology, lending a differences in differences interpretation to resulting indicator values. This framework also allows for decomposition of adaptation to both efficiency and technology change components.

We also extend recent analyses of adaptation and agricultural productivity to consider agricultural production jointly with nitrogen loading, which too can be affected by climate conditions. We construct a new data set, matching historical agricultural production data to nitrogen loading estimates and 30-year climate normals, spanning the years 1987-2012, for the eastern Mississippi River Basin.

Across models, we find productivity gains, driven mainly by technology gains outweighing efficiency losses, over the study period. We also find evidence of average adaptation gains, meaning productivity with climate included increased by more proportionately than without, on average for the study region. This suggests that producers are adapting, both in terms of technical advance and efficiency improvements. Average overall adaptation indicator values are modest, ranging from 0.01 to 2.8 percent, depending on model and period, but when considered in aggregate for agricultural production in the region, imply sizeable gains. Mapping these results also reveals substantial spatial variation in productivity and adaptation, as well as areas of concentration for both gains and losses.

We also note a number of empirical limitations. First, the analysis is aggregated to county-level production and environmental variables, and does not consider individual producer behavior. Related to this, we work with aggregate sales and expenditures, which does not allow for further decomposition of the indicator into input or output mix components, which might shed additional light on adaptation measures. Our main focus in this study is to develop a new adaptation productivity indicator framework. For greater robustness of the empirical results, we could also extend this framework to stochastic frontier estimation of the underlying technology models.

Caveats aside, we believe our developed adaptation productivity indicator framework offers a novel approach to measuring and decomposing producer adaptation to changing climate conditions, while being grounded in economic index theory. This framework can also be extended to include environmental objectives.

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