Factor Markets and Adaptation to Climate Change: Evidence from Minnesota and Wisconsin Farmland Transactions

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Abstract

Land markets allow for the reallocation of economic activity across space and firms, potentially facilitating climate change adaptation. Whether market transactions actually lead to an improved climate response and, if so, how, remains unknown. I combine data on the universe of real estate transaction in Minnesota and Wisconsin with parcel maps and satellite imagery to measure the impact of farmland transactions on productivity, climate adaptation, and adoption of management practices. Transactions almost completely eliminate the negative yield response to extreme temperatures and initiate a gradual 1.5% increase in output per acre. Despite substantial changes in productivity, changes in management practices are minimal. These findings suggest that differences in human capital among farm owners explain a large amount of variation in agricultural productivity and climate sensitivity.

1 Introduction

Factor markets are potentially powerful tools for facilitating climate adaptation. If the market is efficient, climate change induces a reallocation of factors towards better adapted firms and uses at the expense of relatively maladapted employments, and factor prices adjust accordingly (Mendelsohn et al., 1994). In reality, factor markets suffer from distortions that impede allocative efficiency (Hsieh and Klenow, 2009). Whether factor markets actually facilitate climate adaptation is an empirical question that remains poorly understood.

In this paper, I study how farmland transactions alter climate sensitivity of agricultural production in Minnesota and Wisconsin. The agricultural sector is particularly susceptible to climate change (Burke et al., 2024), and moving agricultural production in space, i.e. reallocating agricultural production across land, has the potential to mitigate a large share of climate damages (Costinot et al., 2016; Nath, 2025). At the same time, land markets are thought to be particularly dysfunctional. Evidence from low-income countries suggests that optimal land allocations could generate orders of magnitude greater output (Chen et al., 2023; Aragón et al., 2024). In the United States, agricultural land use is affected by policies such as the biofuel mandate (Scott, 2014), subsidized crop insurance (Obolensky, 2024), and agricultural use value taxation (Borchers et al., 2014). The net effect of these competing forces will play a crucial role in determining how climate change alters American agricultural productivity.

To empirically evaluate whether the farmland market facilitates adaptation, I develop and estimate a simple test. Many crops, including field crops like corn and soy which represent the majority of cropped acres in my sample states, exhibit a strong negative yield response to temperatures greater than 29 degrees C (Schlenker and Roberts, 2009). If buyers are better adapted to climate damages, we would expect parcels to have an attenuated yield response to weather shocks after the transaction. My test mirrors this logic by estimating the within-parcel difference in the yield response to extreme temperature shocks before and after a transaction.

I implement this test using the universe of real estate transactions from Minnesota and Wisconsin matched to parcel boundary maps, satellite imagery, and high resolution daily weather data. In particular, I use the USDA Cropland Data Layer, which classifies the crop planted on each 30m$\times$30m pixel, together with the growing season maximum enhanced vegetation index (EVImax) to measure crops-specific agricultural productivity at the parcel level over the period 2006 - 2023. Previous studies have demonstrated the effectiveness of EVImax as a proxy for agricultural productivity in quasi-experimental research designs (Asher et al., 2023; Wuepper et al., 2023). To validate its use here, I show that EVImax exhibits an approximately linear relationship with county-level yields, that within-county variation in EVImax is associated with yield fluctuations, and that the characteristic yield response curve can be estimated using EVImax in place of observed yields.

My main finding is that a parcel's agricultural productivity becomes insensitive to weather shocks after a transaction. Parcels experience a 0.31% reduction in peak EVI, a remote sensed proxy for yield, per extreme degree day prior to a transaction, slightly stronger than the response on parcels that are not transacted on during the study period. After a transaction, this response drops to -.02% and temperature does not have a statistically significant effect on productivity at any observed value. The difference between these responses is statistically significant (p-value $<$ 0.001) and is increasing in time since the transaction. This finding suggests the market reallocates land towards better adapted farmers and that the scope for this reallocation to mitigate climate damages is substantial.

Given the substantially different temperature responses on the same parcel under buyers and sellers, the question naturally arises of what do these owners do differently. I use a collection of remotely sensed variables and auxiliary datasets to explore other changes that occur on parcels after a transaction. Farmland sales are associated with a gradual increase in productivity unconditional on weather, leveling off at about a 1.5% increase nine years post-transaction, indicating that buyers are (or lease to/hire) more productive operators. Transactions are also associated with dedicating a larger share of the parcel to growing corn or soy, the major agricultural commodities produced in the region. I do not, however, find evidence for the adoption of "climate smart" technologies, such as no-till, cover cropping, or irrigation, in meaningful quantities. Taken together, these findings indirectly suggest that buyers apply traditional inputs more efficiently, both overall and conditional on the weather.

This paper contributes to a growing literature on climate change adaptation (Burke et al., 2024; Carleton et al., 2024) and, in particular, the role of markets in facilitating adaptation (Anderson et al., 2018). Previous research has documented that factor markets for labor, capital, and land all demonstrate responsiveness to weather shocks, indicative of their adaptation potential (Colmer, 2021; Albert et al., 2021; Arteaga et al., 2025). Here, rather than study how factor allocations respond to weather shocks, I show that market transactions allocate land to owners who are better adapted to climate change. The distinction is meaningful, as reallocation prior to the realization of weather shocks will tend to avert a greater share of climate damages.

More broadly, there is a large interdisciplinary literature studying the role of weather shocks and climate change in determining agricultural productivity (Lobell and Di Tommaso, 2025). Many major crops exhibit particularly strong yield sensitivity to high temperatures (Schlenker et al., 2006;

Schlenker and Roberts, 2009), which is hypothesized to occur due to increased water stress (Lobell et al., 2013; Proctor et al., 2022). This yield response has led to a decrease in global agricultural productivity due to climate change (Ortiz-Bobea et al., 2021), and is projected to continue to reduce productivity in spite of adaptation via income growth (Hultgren et al., 2022). A number of agricultural practices ranging from irrigation (Schlenker et al., 2006) to cover cropping (Aglasan et al., 2024) have been shown to moderate the negative effects of extreme temperatures on agricultural productivity, and spurring adaptation is seen as a global food security policy priority (Lobell et al., 2008). I contribute to this body of research by demonstrating the role of producer heterogeneity in determining the sensitivity of yield to high temperatures and exploring the management practices associated with improved adaptation.

My focus on the effects of farmland transactions on output and resilience to shocks ties this study to a vast literature on factor misallocation (Restuccia and Rogerson, 2017). A number of studies explore the role of land allocations in determining aggregate agricultural productivity (Adamopoulos and Restuccia, 2014; Chen et al., 2023; Aragón et al., 2024). Similar to Gollin and Udry (2021), I study how production shocks contribute to differences in productivity across farms. Whereas they conceive of shocks as an exogenous source of productivity variation that does not necessarily affect the ex-ante efficient allocation of land, but may appear to be misallocation ex-post, I explicitly consider the role of the land allocation in determining productivity responses to shocks.

The remainder of the paper is organized as follows. In Section 2 I describe the data used in the analysis. Section 3 elaborates the test for climate adaptation via land market transactions and presents the main results. Section 4 explores the other changes that occur on a parcel after a transaction. Section 5 concludes.

2 Data

This paper makes use of three main collections of data. The first is real estate transaction records and parcel boundary maps which allow me to identify when and where changes in farmland ownership take place. The second is remote sensing and additional geospatial data that measure agricultural productivity, crop choice, and management decisions. The third is high resolution daily weather data that provides the necessary variation for implementing my empirical test. I describe each source below.

2.1 Transaction Records and Parcel Boundaries

Minnesota and Wisconsin provide an ideal setting in which to study farmland transactions thanks to real estate data publication and parcel boundary mapping initiatives in both states. While real estate transaction records are public data in most places in the United States, access is often granted through individual county clerk offices, making the collection and homogenization of transaction data costly and difficult. Existing real estate transaction products typically focus on the residential housing property market. Minnesota and Wisconsin both publish the universe of real estate transactions, homogenized across counties.

In Minnesota, data from 2010-2021 was published through a collaboration between the state Department of Revenue and the University of Minnesota Department of Applied Economics (Lazarus, 2022). Lazarus (2025) describes how these data are processed for yearly analysis of farmland sales in the state, and where relevant I follow his recommendations. Similarly, the Wisconsin Department of Revenue publishes records of all arm's-length real estate transactions in the past five years. I use data from 2019-2024 in the present analysis.

An important caveat to the use of these data is that, while they report the universe of arm's-length transactions, there is reason to believe that the number of farmland transactions which do not meet this criterion is substantial. In particular, only slightly more than 50% of agricultural land operated in 2007 in the United States was purchased in an arm's length transaction (Nickerson et al., 2012). Large shares of farmland are inherited or purchased from relatives. Due to the nature of the data, I am limited in my capability to study these other kinds of transactions.

Crucially for this study, transaction records almost invariably list the parcel identifier associated with the sold property. This allows me to link sales to parcel boundaries. Again, Minnesota and Wisconsin are uniquely amenable to data collection thanks to statewide parcel boundary mapping initiatives in both states, which harmonize maps across counties and, in the case of Wisconsin, provide updated tax roll information approximately every year.

I attempt to merge all transaction records to parcel boundaries and retain for analysis matches in counties with at least 85% merge success rate. The sample of counties included in my analysis along with examples of individual counties showing the set of agricultural parcels and those that are transacted on is shown in figure 1. Many counties in Minnesota are missing due to not currently meeting requirements for inclusion in the statewide parcel map nor providing a usable map through the county website. A far smaller share of counties are missing in Wisconsin. There, missingness arises due to different parcel identification systems between the parcel map and real estate transaction records or redaction of parcel identifiers. In total, data from 107 counties and over 1 million agricultural parcels is included in the analysis sample, with over 25,000 parcels transacted on.

2.2 Remote Sensed and Geospatial Outcome Data

Outcomes for most analyses I conduct are derived from Landsat satellite imagery. The sensors aboard Landsats 5, 7, 8, and 9 capture 30 m resolution imagery with a nominal revisit time of about 16 days. The imagery produced by all of these sensors is multispectral, meaning that additional segments, or "bands," of the electromagnetic spectrum aside from the visible red, green, and blue bands are recorded as extra channels of the imagery. These additional bands, such as near infrared and shortwave infrared, are particularly useful for measuring agricultural outcomes via the construction of a number of vegetation indices.

The most import index for this study is the enhanced vegetation index (EVI), which I use as a measure of agricultural output per unit area. EVI is an adjusted version of the more widely known normalized difference vegetation index (NDVI) that is more sensitive to changes in biomass in areas with dense vegetation, making it particularly suitable to agricultural monitoring in highly productive regions such as the American Midwest.

Letting $p(j)$ index pixels' location in space and j index images, the more standard NDVI is calculated as

$$NDVI_{p(j)} = \frac{NIR_{p(j)} - Red_{p(j)}}{NIR_{p(j)} + Red_{p(j)}} \tag{1}$$

where NIR is the radiance of the near infrared band and Red is the red band. The construction of NDVI is based on the fact that chlorophyll absorbs visible spectrum light, like the red band, but reflects near infrared light to protect the plant's biology. Correspondingly, a multispectral sensor capturing imagery of healthy crop biomass tends to record a high value for reflected near infrared light, but a low value for red band light. As the difference in the numerator of (1) grows, the NDVI value approaches 1, so greater biomass appears as a high NDVI value. As the difference grows in the opposite direction, NDVI approaches -1, though in practice NDVI typically ranges between 0 and 1 on land.

EVI augments (1) with additional information from the blue band and applies a number of scaling factors to produce an atmospherically corrected, more sensitive measure. The formula for EVI is given by

$$EVI_{p(j)} = G\frac{NIR_{p(j)} - Red_{p(j)}}{NIR_{p(j)} + C_1 Red_{p(j)} - C_2 Blue_{p(j)} + L} \tag{2}$$

where $Blue$ is the blue band, and G, C_1, C_2, and L are constants used to increase sensitivity to changes in biomass, correct for atmospheric distortions, and reduce noise (Jiang et al., 2008). The most commonly used values are $G = 2.5$, $C_1 = 6$, $C_2 = 7.5$, $L = 1$, and I use those values here. EVI has been shown to be approximately linearly related to the leaf area index (Boegh et al., 2002), a measure of crop biomass, making it a very useful proxy for land productivity.

The other vegetation index I make use of for analysis is the normalized difference tillage index (NDTI), a proxy a widely practiced "climate smart" technique called no-tillage. The NDVI formula is similar in structure to that of NDVI, it is a normalized difference between two bands so values are constrained to lie in $[-1, 1]$. The distinction lies in the bands that are included,

$$NDTI_{p(i)} = \frac{SWIR1_{p(i)} - SWIR2_{p(i)}}{SWIR1_{p(i)} + SWIR2_{p(i)}} \tag{3}$$

where $SWIR1$ and $SWIR2$ are two bands measuring different segments of the short wave infrared spectrum. The "shorter" (i.e. higher frequency) SWIR1 band is reflected relatively strongly by crop residues, which are associated with weakened tillage intensity. NDTI has been shown to have a strong linear correlation with crop residue cover share (Zheng et al., 2012), and thus makes an effective proxy for reduced tillage.

I make use of two additional measures of derived from Landsat imagery that are less striaght-forward to describe, as they both make use of predictive machine learning models to produce their output. The first is the Cropland Data Layer (CDL), a product produced by the USDA's National Agricultural Statistics Service (NASS). The CDL uses Landsat imagery along with additional land use/land cover data to predict crop type using a decision tree model trained using ground truth data collected by the USDA (Boryan et al., 2011). The CDL is particularly skillful at predicting major crops like corn and soy, which are the focus of this study, exhibiting classification accuracy in excess of 85%.

The second is cover cropping utilization, predicted using a modified version of the random forest classifier developed by Seifert et al. (2018). I utilize the same ground truth dataset and basic modeling approach, but adjust the set of features used to predict cover cropping. In particular, I only use imagery-derived features, such as band reflectance values and vegetation indices, and omit additional features such as weather variables. The rational for this change is that I am interested in understanding how management choices may alter the temperature-yield response function, and thus do not predict cover cropping using weather variables to avoid a "bad control" problem. Despite having access to fewer features, my model exhibits considerable skill, predicting cover cropping status with 93% accuracy.

2.3 High Resolution Daily Weather

Agronomic and observational studies have demonstrated that, for major field crops like corn and soy, each additional degree-day spent above a certain threshold (typically 29 or 30 degrees C) during the growing season inflicts a large negative yield penalty, whereas moderate temperatures tend to slightly increase productivity (Schlenker and Roberts, 2009; Lobell et al., 2011, 2013). Accurately measuring exposure to these temperatures requires weather data that is both highly spatially and temporally resolved. To that end, I utilized the daily 2.5 arc minute (slightly less than 5 km) resolution PRISM dataset. I follow Schlenker and Roberts (2009) in approximating growing degree days using a sinusoidal interpolation between daily minimum and maximum temperature. I use two different temperature bins, approximately corresponding to the regions of slight increase (0 - 29 degrees C) and steep decline ($\geq$ 29 degrees C) in yield response found in previous studies. I refer to these as growing degree days (GDDs) and extreme degree days (EDDs), respectively.

3 An Empirical Test for Market-based Adaptation

My empirical test for climate adaptation via farmland transactions analyzes changes in the temperature-yield response on a parcel around the time of a transaction. In particular, I follow Schlenker and Roberts (2009) in specifying the response function as log-linear in growing degree days, extreme degree days, total precipitation and its square. Where this specification differs is in allowing the coefficients associated with all weather variables to vary depending on the transaction status of a parcel. Another difference in my approach is my utilization of design-based causal inference techniques to isolate exogenous variation in the weather variables of interest.

Concretely, consider the specification estimated by Schlenker and Roberts (2009):

$$\begin{aligned} \ln(Yield_{i,t}) = & \alpha_i + \delta_t + \eta_i t \\ & + \beta^{GDD} GDD_{i,t} + \beta^{EDD} EDD_{i,t} \\ & + \Gamma X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where X includes total growing season precipitation and its square.

The "design-based" interpretation of this specification is that the fixed effects and trend parameters, α_i, δ_t, and η_i, model the selection into weather realizations in the sense that they span the variation in the expected value of the weather variable vector, conditional on potential outcomes (Borusyak and Hull, 2024). An implication is that the residuals of the weather variables projected on unit and time dummies and unit dummies interacted with the year are mean-independent of the structural errors. This is the property that allows for identification of a "causal effect."

Note that outcome data is unnecessary for implementing this residualization. Indeed, it is not even necessary to have a panel of outcome data; so long as one has access to a panel of weather data, it is possible to residualize the weather realizations in the cross-section with available outcome data and estimate the causal effects in that cross section, since the residual variation in weather is as good as randomly assigned. Indeed, if the fixed effects and trends are a good model of the conditional expectation of weather, this corresponds to the re-centering solution proposed by Borusyak and Hull (2023).

While I have access to a panel of outcomes, it is relatively short at 15 years in Minnesota and 18 years in Wisconsin. Rather than estimate everything in a single regression, I opt to use a longer panel of weather data, 1980-2023, to isolate exogenous variation in weather realizations and then estimate the parameters of interest using the residualized weather variables. To this end, let $\tilde{Z}$ denote the residuals of Z projected on unit and year dummies and a unit trend. I estimate

$$
\begin{aligned}
\ln(EVImax_{i,t}) = {} & \nu_t^{GDD}\widetilde{GDD}_{i,t} + \nu_t^{EDD}\widetilde{EDD}_{i,t} && (5)\\
& + \beta_{pre}^{GDD}\widetilde{GDD}_{i,t}1\{E(i) < t\} + \beta_{pre}^{EDD}\widetilde{EDD}_{i,t}1\{E(i) < t\} && (6)\\
& + \beta_{post}^{GDD}\widetilde{GDD}_{i,t}1\{E(i) \geq t\} + \beta_{post}^{EDD}\widetilde{EDD}_{i,t}1\{E(i) \geq t\} && (7)\\
& + \tau 1\{E(i) \geq t\} && (8)\\
& + \Gamma X_{i,t} + \alpha_i + \varepsilon_{i,t} && (9)
\end{aligned}
$$

where i indexes parcels, t indexes years, and $E(i)$ denotes the year parcel i is transacted on (if ever). The parameters ν_t^{GDD}, ν_t^{EDD} allow the effect of growing degree days and extreme degree days to differ by year in the set of parcels that are never transacted on. This is potentially important for capturing gradual adaptation that is occurring in the background. Since the set of observations for which $1\{E(i) \geq t\} = 1$ mechanically tend to be later in the sample, if there were gradual adaptation, but we enforced homogeneous effects of temperature throughout the panel in the never-transacted parcels, we might wrongly conclude that transactions induce adaptation simply because $1\{E(i) \geq t\}$ would proxy for background adaptation that is occurring on all parcels.

The parameters of interest are β_{pre}^{GDD}, $\beta_{post}^{G}DD$, β_{pre}^{EDD}, β_{post}^{EDD}, which represent the additional effects of growing degree days on transacted parcels before and after a transaction and the effects of extreme degree days before and after a transaction, respectively. If β_{pre}^{GDD} or β_{pre}^{EDD} is different from zero, it implies that there is selection into market transactions on climate sensitivity under buyers. For example, a negative estimate of β_{pre}^{EDD} suggests that parcels that are particularly sensitive to extreme temperatures when operated by their sellers are more likely to be involved in transactions, perhaps indicative of relatively maladapted owners being more willing to sell. In contrast, one interpretation of a positive estimate would be that buyers seek out parcels that have characteristics that make production on them relatively insensitive to climate.

Similarly, if β_{post}^{GDD} or β_{post}^{EDD} is different from zero, it implies that parcels are differentially sensitive to weather after a transaction when compared to parcels that are not involved in transactions. If the sign of one of these parameters aligns with that of its corresponding pre-transaction parameter, it is perhaps indicative of selection of parcels into the market, rather than buyers in sellers. In contrast, differing signs suggest that buyers and sellers differ in how they operate a parcel, in a way that leads to different climate sensitivity.

The parameter τ measures level differences in expected productivity between buyers and sellers. Interpretation of this parameter is somewhat obfuscated by its nature as a difference-in-differences-style estimate. A positive value indicates that expected productivity is greater under buyers than under sellers, but it is unclear whether parcels are negatively or positively selected into the market.

Finally, the control variables X include the residualized precipitation variables, allowing for varying effects in each year for parcels that are never transacted on, and their interactions with the pre- and post-transaction indicators. The unit fixed effect α_i is included as an efficiency control, to absorb variation in level differences in outcomes between parcels that would otherwise be included in the error term.

The results of this estimation are shown in Figure **??**. To assist in interpretation, I have averaged the ν_t parameters to allow them to be plotted as the "typical" temperature response curve, labeled "Never Transacted." Reassuringly, the estimated response function is quite close to that of Schlenker and Roberts (2009), both in shape and magnitude. While temperatures up to 29 C are associated with modest increases in productivity, extreme temperatures are associated with steep declines. A single day at 35 C is estimated to reduce yield by 1.4% for never-transacted parcels.

Turning to transacted on parcels, the effect of extreme degree days is slightly more strongly negative prior to a transaction compared to never-transacted parcels, i.e. they are more sensitive to high temperatures. While this effect is statistically significant (p-value=0.02), it is quantitatively small and the response curve for pre-transaction parcels is quite close to that of never-transacted parcels. In contrast, the extreme degree day response for post-transaction parcels is much weaker, leading to an almost completely flat temperature response. There is no observed temperature in the sample at which the estimated temperature-yield response post-transaction is statistically significant from zero. And while the estimated response is substantially noisier at higher temperatures, we can reject that the yield response is the same pre- and post-transaction at temperatures greater than 33 C with 5% significance or less.

This result is striking. Transactions move parcels that are relatively more sensitive to extreme temperatures to owners who almost completely eliminate the extreme temperature response. At the same time, productivity increases on transacted parcels by 1.3% on average after the sale. These findings suggest that the farmland market moves land away from less productive, relatively maladapted farmers towards more productive farmers who are much better equipped to handle extreme temperatures. The magnitude of these changes naturally begs the question of what new owners change with regards to management to achieve such better production outcomes.

4 Changes in Management After Transactions

To explore changes in management, I use a spatial fixed effects event study design. In a spatial fixed effects design, the control group is constructed from units that are very close to the treated unit of interest in space. The advantage of this design over more traditional event study estimators is that it allows for wide heterogeneity in time trends across space that do not need to be explicitly modeled, so long as units that are close experience similar trends. To overcome issues identified with traditional event study estimators stemming from "bad comparisons," I restrict the control group for each transacted on parcels to be those parcels within 3 km that have never been transacted on, such that all controls are "pure controls."

Concretely, let $\mathcal{N}(i)$ denote the set of parcels within 3 km of i that are never transacted on. I estimate regressions of the form

$$Y_{i,t} - \frac{1}{|\mathcal{N}(i)|} \sum_{j \in \mathcal{N}(i)} Y_{j,t} = \alpha_i + \sum_{h=-10}^{13} \beta_h 1\{E(i) - t = h\} + \varepsilon_{i,t} \tag{10}$$

where Y is the outcome of interest. The β_h parameters trace out the dynamic treatment effects, with negative values of h used to test the parallel trends assumption necessary for causal identification.

Results are shown in Figure 3. As noted earlier, productivity rises, eventually reaching 1.5% above pre-transaction levels, but this rise occurs gradually, only leveling off after 9 years. New owners also shift to growing more corn and soy, devoting about 2% more of the parcels area to those staples, though this too continues to rise in the years after a transaction. Where there is less evidence is on the utilization of no-till or cover cropping. If anything, it appears that adoption of these “climate smart” technologies declines post-transaction, though the magnitudes are quite small.

5 Conclusion

Reduced form evidence of the effects of extreme temperatures on yields before and after a parcel of farmland is sold suggests that factor markets can play in important role in climate adaptation. While parcels exhibit slightly stronger than average extreme temperature responses prior to a transaction, new owners almost completely eliminate the negative effects of high temperatures while increasing expected productivity. These results suggest that the market is effective at moving land away from less productive, poorly adapted farmers towards better adapted and more skillful producers.

It is unclear, however, what management practices drive these results. New owners do not adopt more cover cropping or no-till, and even appear to dis-adopt these technologies slightly, or at least not adopt them as quickly as neighboring farmers. Given this, it seems plausible that the human capital embodied in new owners explains such a radical change in outcomes post-transaction.

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Figure 1: Sample Counties

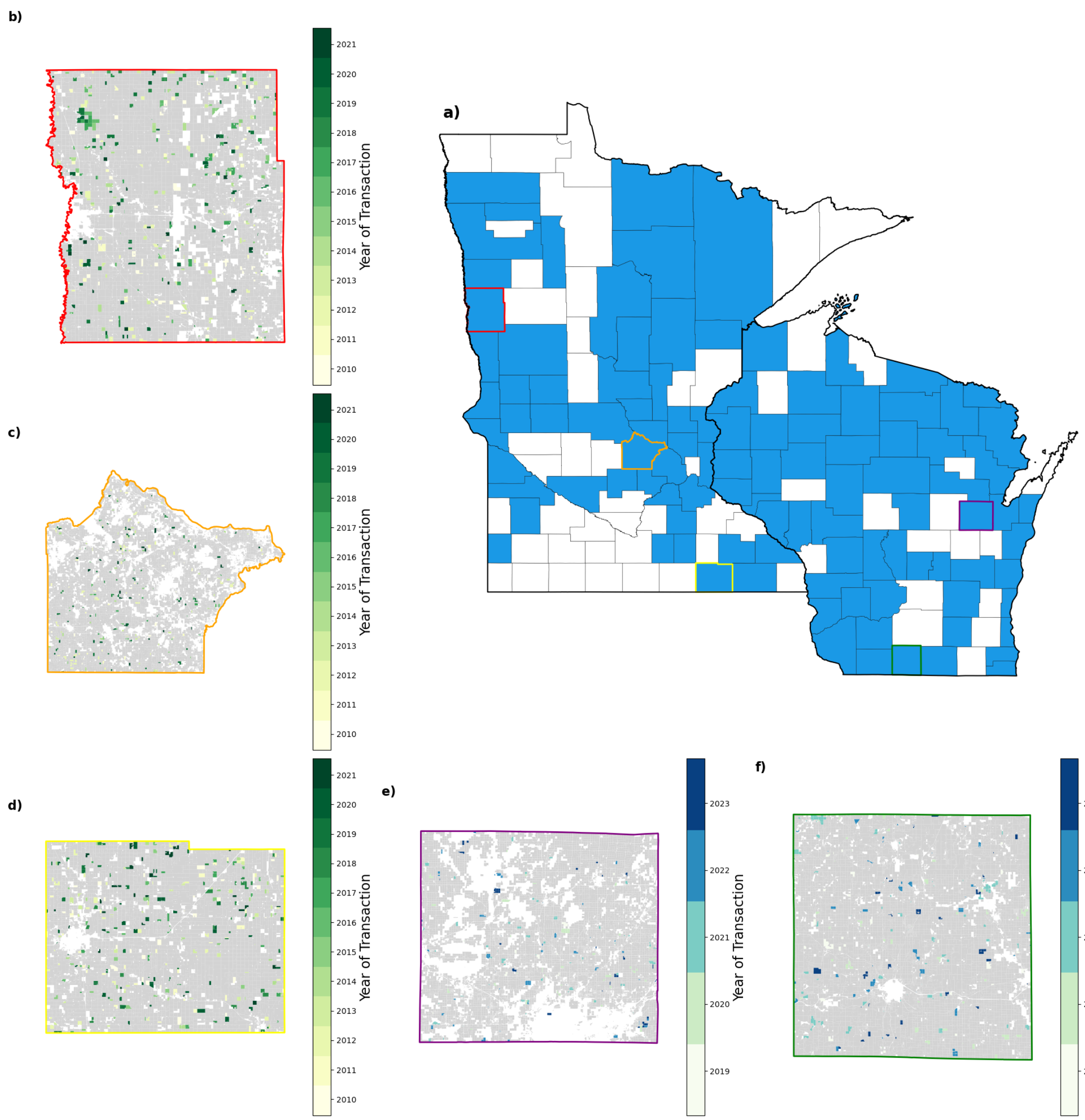

Figure 2: Yield Response to Temperature Pre- and Post-Transaction

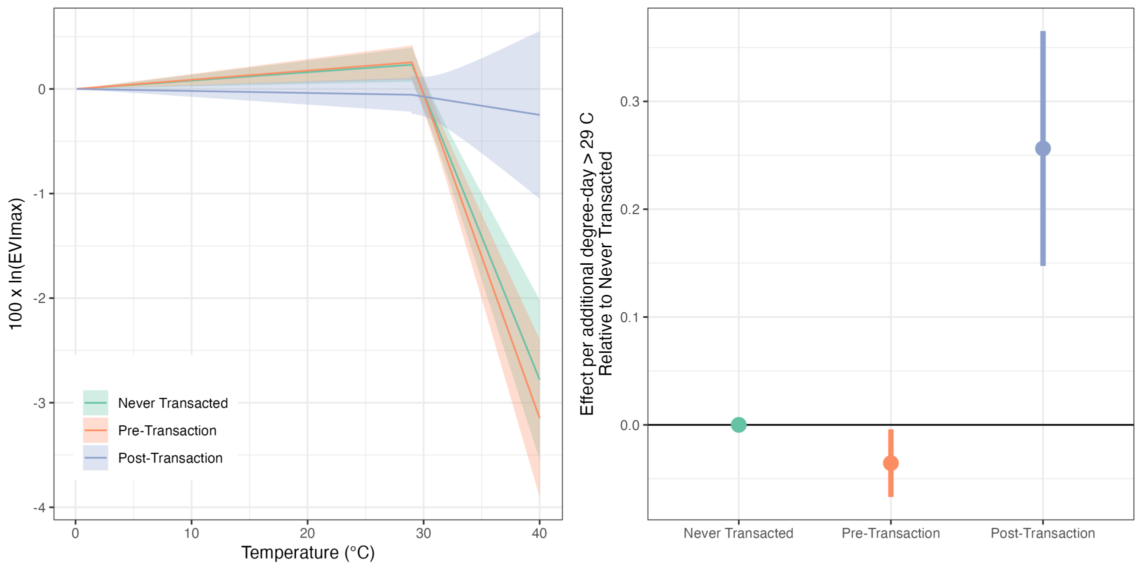

Figure 3: Yield Response to Temperature: Event Study