Reassessing the Effects of Weather on Agricultural Productivity

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Paul Samuelson mused that "…there is nothing sacred about the conventional boundaries of economics; if the [business] cycle were meteorological in origin, economists would branch out in that direction (1947, p. 316)." Indeed, weather has all sorts of important economic effects, and economists have not shied away from considerations of weather or its longer run manifestation, climate.[1] In fact in more recent years, economists have given renewed attention to the effect of weather and climate on agricultural productivity as concerns over climate change and its effect on global food security have intensified.[2]

While weather affects health outcomes, transportation systems, energy demand, and a whole host of other important systems, it is especially important in agriculture. Agricultural production is a biological process directly affected by weather (e.g., frosts, droughts, floods, and heat stress), as well as indirectly through effects on pests and diseases that undermine crop productivity. Many agricultural productivity assessments done by economists to date have included various weather variables in statistical yield models to control for location effects of weather and prognosticate about the impact of climate change. Most assessments include raw weather variables (e.g., temperature and rainfall for certain months) to explain yield variation across time and space. These analyses often use variable selection procedures based solely on statistical explanatory power making them prone to spurious results. For example, a surprising amount of work seeks a set of monthly weather variables that best correlate with yields, but by design "…tend to introduce a certain circularity by defining bad weather as that which is associated with poor yields (Garcia et al. 1987, p. 1096)."

In accounting for the productivity consequences of weather, economists typically rely on weather metrics that are too coarse either temporally or spatially to meaningfully capture their productivity effects—constituting a type of joint temporal and spatial aggregation bias one could call "biological aggregation bias." For example, average annual or even monthly rainfall or temperature misses the mark insofar as hour-to-hour, day-to-day, and week-to-week variations in these attributes all affect plant

1 NASA (2013) notes that "[t]he difference between weather and climate is a measure of time. Weather is what conditions of the atmosphere are over a short period of time, and climate is how the atmosphere "behaves" over relatively long periods of time."

2 The literature on the economics of weather and climate change is growing quickly in both scope and scale. Economists have recently concerned themselves with topics as diverse as the effects of climate change on (to name but a few): birth weight (Deschênes 2009), damages from increased intensity and frequency of tropical cyclones (e.g., Mendelsohn et al. 2012), market effects (e.g., Ciscar et al. 2011), and economic growth (e.g., Eboli et al. 2010). Further, there is a vast environmental economics literature on the indirect effects of climate change manifested via mitigation policies.

growth. Moreover, there is a path dependency in the productivity consequences of weather phenomena, so precisely when in a plant's growth these variations occur is important—e.g., heat stress at early growth stages of corn has a different effect on yield than an identical weather event at the tasselling stage.[3] Consequently, matching variables to the calendar month fails to represent when within the crop's growth important events occur.

Most studies also consider weather as an exogenous influence on crop yields and production. But, the weather most relevant to crop productivity is endogenously dictated by farmer decisions on when and even where to plant crops over both shorter and longer periods of time. For example, in 2007 Texas corn farmers had planted over half of their acres by the first week of April, while Iowa corn farmers waited, on average, a month longer (USDA, NASS 2011). Moreover, the estimated planting date in, say, Dodge county Minnesota ranged from April 22 in 1987 to June 14 in 1909, with similar inter-seasonal variation occurring elsewhere in the United States. Alternatively, Beddow and Pardey (2014a) show that the spatial footprint of U.S. corn production has changed substantially over the past century and more as farmers shifted where they planted corn, meaning that the climate actually affecting the crop has changed simply as a consequence of that movement. Indeed, at the extreme, some agricultural crops are grown in greenhouses essentially eliminating the influence of weather altogether. Thus, an understanding of both the economics *and* biology of crop production are required to construct sensible representations of weather for productivity assessment purposes.

Our objective in this paper is to explore the effect of weather on long-run variation in U.S. corn yields in light of intensification in the use of purchased inputs such as improved seed, irrigation, and fertilizer that occurred from 1879 to 2007. To accomplish this objective, we step beyond the existing literature by developing a new methodology for constructing bio-economic indexes of "agricultural weather" and apply it to a long-run series of U.S. weather, corn production and yields. Our index is conceived and constructed at a sufficiently granular spatial and temporal scale to minimize, or at least reduce, the biological aggregation problems (and the associated economic endogeneity) inherent in most previous attempts to incorporate weather variables into crop productivity models. We then use spatial econometric methods to examine the effects of weather on crop yields and especially the interaction between input intensification and weather. Rather than treating weather as a disturbance to the status

[3]Corn's vegetative stage ends with the formation of tassels (the pollen-producing male flowers) and the reproductive (grain fill) stage begins with the formation of silks (the female flowers

quo that must be "corrected for" (or treated simply as part of a statistical residual), we view it as a natural input, on par with purchased inputs such as improved varieties and fertilizer.

Our results provide further evidence that the pervasive professional and popular concerns about the global effects of climate change on crop yields and global food supplies are likely overblown to the extent that changes in crop biology and farmer behavior are ignored.[4]

I. Weather and Agricultural Productivity

The contemporary economics literature relating weather to agricultural productivity has largely focused on the potential effects of climate change, including several high-profile studies that focus on the environmental determinants of crop yields and land rents (for example, Mendelsohn et al. 1994; Lobell and Asner 2005; Schlenker et al. 2006; Schlenker and Roberts 2009; Ashenfelter and Storchmann 2010; Hidalgo et al. 2010 and Deschenes and Greenstone 2012). Critically, Mendelsohn et al. (1994) pointed out that most studies fail to account for farmers' ability to adjust to changing situations, implicitly employing a "…dumb farmer scenario (p. 753)." In various reports, Mendelsohn and colleagues sought to address this deficiency by estimating the effect of weather on farm land rents and revenue (but not crop yield *per se*), thus implicitly allowing land to be repurposed (perhaps even out of agriculture) as climate regimes change. The results showed smaller prospective climate change impacts on land rents than have generally been predicted. However, if agricultural productivity and yields are of concern, one must disentangle the direct effect of weather from the effects of other factors.

The recognition that farmer behavior has an important role in determining the effect of climate change on agricultural productivity is important. Yet, many subsequent studies still ignore this fact. For example, Lobell and Asner (2003) studied the effect of climate change on agriculture by assessing yield trends for selected U.S. counties from 1982 to 1998 using a linear regression of the change in yield on the corresponding change in the average of daily June through August temperatures. Since temperatures fell over the period in the majority of the selected counties, the authors found that changes in temperature had a positive effect on crop yields. Lobell and Field (2007) assessed the relationship between climate change and national average yields from 1961 to 2002 for several crops globally. To derive the seasonal

4 For example, the recently released IPCC report states that "With or without adaption, climate change will reduce mean yields by 0 to 2% per decade for the rest of the century compared to a baseline without climate change (Field et al. 2013, p. 22)."

average temperature and rainfall for a crop, the authors used the notion of a "global growing season" defined as the period during which precipitation and temperature were most highly correlated with yield.

One possible reason many studies continue to ignore the importance of farmer behavior is that Mendelsohn et al.'s solution of using land rents or revenue to implicitly account for farmer behavior has its shortcomings. For example, while weather is a major factor in crop productivity, especially for dry land production systems, and crop productivity influences farm land rents and revenues, there are many other direct and indirect weather effects on farm land rents and revenues that can confound interpretation.

There is a long history of economic studies exploring the effect of weather on yields that predate contemporary studies focused on climate change. For example, Smith (1904 and 1914) plotted monthly rainfall against corn yields for a number of U.S. states and concluded that July precipitation is the most important determinant of corn yields. Smith's methodology of looking for weather variables that are most highly correlated with yields has echoed through the literature for more than a century. While the statistical tools have become increasingly sophisticated, the rationalization of the methodology has not. More recently, Stallings (1960) developed "weather indexes" by asserting departures from the linear yield trend are due to weather, which is also an approach still commonly used in the literature today.

Mendelsohn et al. has not been the only critique of this literature and the importance of farmer behavior has not been the only point of criticism. For example, a reasonable explanation for Smith 's finding of the importance of July weather in determining corn yield is that July happens to coincide with the typical date of silking in the U.S. Corn Belt, a growth stage in which the plant is particularly vulnerable to drought stress. Wallace (1920) argued that it would be difficult find a set of raw weather variables that consistently explain yields over multiple states or counties—an argument supported by Mattice's (1931) finding that the set of monthly weather variables that best explained yields was different for each state.[5] Alternatively, Plaxico (1961) objects to the indexes developed by Stallings arguing that they essentially re-label unexplained variation as an explanatory variable. Katz (1977) similarly objects to these common "statistical black box" methods, noting that they are subject to spurious, uninterpretable results—should higher temperatures (on average or in any particular month) lead to higher or lower yields, and how is any temperature response likely to change with precipitation (on average or in any particular month)?

[5] By extension, use of raw weather variables in cross-country assessments of yield performance are similarly problematic.

Other criticisms include the reflections of Shaw (1964) on the problems with trying to use spatially aggregated weather to explain yields given the inherent variability of weather across space. Temporal aggregation is equally problematic with Kaufmann and Snell (1997) pointing out "[t]he effect of climate on yield depends on the phenological stage of crop development rather than the chronology of the human calendar (p. 179)." Together these arguments provide a compelling reason why studying the relationship between weather and yields is best conducted at the smallest possible spatial and temporal scale of aggregation, so the spatio-temporal, biological processes through which crops convert temperature, rainfall and other inputs into yield can be considered explicitly.

Thus, to the extent recent studies of the effect of climate change on agricultural productivity continue to rely on detrended yields, raw weather variables aggregated over biologically and behaviorally insensitive spatial and temporal units, or the assumption of a temporally and spatially invariant growing season, they do not represent a major empirical or conceptual departure from the literature dating back to Smith and Wallace.

II. Data

Our analysis of the effect of weather and intensification on U.S. corn productivity relies on temporally and spatially disaggregated yield information, a gridded weather surface for the entire United States (with monthly temperature and precipitation data at a 30 arc minute resolution), a newly constructed bio-economic weather index, and measures of the extent of input intensification that accompanied improved seed, irrigation, and fertilizer adoption from 1879 to 2007.[6] In this section, we detail what specific data were used as well as how they were used.

Corn Yield

Long-run county-level U.S. corn area and yield data are available from two sources: the USDA's National Agricultural Statistics Service (NASS) and various agricultural censuses. While the NASS data are collected on an annual basis, they do not provide coverage of all counties in all years and the geographical extent of the coverage has varied over time, which is problematic for the objectives of our analysis. For example, if the data coverage is biased towards counties where corn production is relatively important

[6] The results we find for U.S. corn are not necessarily indicative of the climate-yield relationships for other crops in the Unites States or other countries. That's said, as Beddow and Pardey (2014, p. 4) observe "U.S. corn production is worthy of attention in its own right. In 2011, corn constituted 34 percent by weight of global cereal output, and the United States alone accounted for 36 percent of the world's entire corn crop (FAO 2013)."

and suitable weather is endogenous to farmers' decisions, the analysis risks ignoring information on locations that are relatively less suitable for production. Alternatively, the various agricultural censuses are conducted less frequently (about every five years), but provide more complete spatial coverage, which is why they were chosen. The agricultural censuses provided 23 years of data stretching back to 1879, the first year in which both area and yield were reported, and continuing to 2007 when the latest available agricultural census was conducted. A challenge working with these data (as well as the NASS data) is that county boundaries have changed over time, so the data were transformed to reflect year-2000 county boundaries (Beddow 2014) providing a consistent, unbalanced panel of corn area and yield data over a 128 year period.

Bio-Economic Weather Index

Construction of our new bio-economic weather index (BWI) for corn is described in detail in Beddow (2014). The BWI is based on a parsimonious crop model that represents the important phenological events in the crop's lifecycle. The model is combined with spatio-temporal information on temperature and precipitation to characterize the suitability of observed weather for corn development in each county and year based on phenologically specific indexes. These indexes are then used to obtain the BWI—a value on the unit interval where higher values represent more suitable annual weather conditions for corn grain yield.

Several sources of data were used to construct a long-run time series of U.S. weather. Minimum, maximum and mean temperatures on a monthly 30 arc minute grid for 1901 to 2005 were obtained from the Climate Research Unit (CRU) at the University of East Anglia. Maximum and minimum temperatures for 2006 and 2007 on a daily 30 arc minute grid were available from NOAA (NOAA-CPC 2011 a, b and c). Precipitation for 1900 to 2007 was obtained from the Center for Climate Research at the University of Delaware (Matsuura and Wilmott 2009). Since there were no gridded weather data available for the United States prior to 1900, additional work was necessary to convert weather station data from NOAA's Global Historical Climate Network (GHCN) (NOAA-NCDC 2007). This conversion was accomplished by estimating the relationship between available gridded and weather station data, and using this relationship to interpolate gridded temperature and precipitation data prior to 1900. The gridded data were aggregated to the county level by averaging cell values in each county weighted by corn production area. Thus, the weather data are specific to corn production and need not be appropriate for use with other crops.

The methods used to transform these weather data into the BWI were inspired by the CLIMEX model (Sutherst and Maywald 1985). CLIMEX is a parsimonious model that infers the response of a species to climate from its geographical distribution and seasonal patterns of growth and mortality in different locations. In the CLIMEX modeling framework, the aim is to define the regions that a species could potentially occupy and thrive by characterizing the response of the species to various climatic factors. The CLIMEX model suggests a particularly attractive and practical methodology for estimating the effect of weather on crop yields for use in a variety of economic contexts.

The suitability of weather for corn was characterized for three distinct and important stages of development: vegetative, silking, and reproductive. For each county in the United Sates, the timing of each stage was estimated dynamically based on both farmer behavioral and crop biological responses to weather. The initiation of the vegetative stage, crop emergence, was assumed to occur at 69 growing degree-days (using a base of 10^{o}C) or 30 calendar days after planting, whichever was shorter. Accumulated growing degree days were calculated by integrating the sine curve between (potentially non-binding) lower and upper temperature thresholds using formulae provided by Baskerville and Emin (1969) and Zalom et al. (1983). To determine the planting date three conditions had to be met. First, at least ten growing degree-days had to accumulate in order for soil temperatures to warm enough for planting corn. Second, the 60th Julian calendar date had to be surpassed, which is the earliest corn planting is typically observed in the United States (see USDA-NASS 1997). Third, soil saturation had to be below 100 percent, so fields would be dry enough for farmers to avoid soil compaction and equipment issues. Soil saturation was assumed to occur when soil moisture reached 150 mm where soil moisture was calculated based on the model reported in McCabe and Markstrom (2007). This model takes into account temperature, precipitation in the form of snow and rain, evapotranspiration, and runoff. After emergence, the length of the vegetative stage was determined using daily crop growth characterized by the temperature and a beta distribution with parameters reported in Streck et al. (2008). Once cumulative growth surpassed a temporally and spatially invariant threshold, the silking stage was assumed to begin. The lengths of the silking and reproductive stages were then calculated based on growing degree-day models.

Moisture and temperature have differential impacts on corn development during the three stages of growth we considered. Therefore, separate moisture and temperature suitability indexes for corn production were developed for each. The soil moisture indexes used daily soil moisture estimates with the piecewise linear functions reported in Morgan et al. (1980). Daily index values were averaged within a stage to aggregate the index to a single value. To account for differences in moisture due to irrigation, irrigated areas were given a moisture index of one, ideal moisture for corn development, and a weighted average based on the proportion of irrigated area was taken between this ideal moisture value and the value attributable solely to weather.

The temperature suitability index was assessed separately from the phenological responses to temperature. Following the CLIMEX methodology, daily temperature cycles were represented by a sine curve fitted to the estimated maximum and minimum daily temperatures (Sutherst and Maywald 1985). This daily cycle was used with four different growth response parameters, the lower and upper temperature limits for plant growth and the optimal temperature range, to construct the temperature index. Corn growing degree-days are usually calculated based on a lower limit of 10^{o}C and upper limit of 30^{o}C, which were the values selected to represent boundaries of optimal corn growing temperatures. The temperature index for each stage increased when the average daily temperature was in this range. Contrary to the usual growing degree-day model, we assumed temperatures below or above this optimal range are detrimental to corn development. Therefore, the temperature index was decreased by 20 percentage points for each degree the average daily temperature was below 10^{o}C and 10 percentage points for each degree the average daily temperature was above 30^{o}C until the temperature index reached zero. These assumptions imply lower and upper plant growth temperature limits of 0^{o}C and 40^{o}C. As with the moisture index, the temperature index was calculated on a daily basis and averaged for each phenological stage.

The final step was to aggregate the six phenologically distinct indexes. Several alternatives were considered including linear aggregations with and without multiplicative interactions. Intuitively, interactions between temperature and moisture suitability are just as likely as interactions across the various phenological stages of corn development given the cumulative effects of weather. Therefore, we ultimately settled on a parsimonious multiplicative aggregation.

Improved Seed, Irrigation, and Fertilizer Adoption

It is clear from the literature that understanding the processes underlying yield require some accounting for the adoption of new technology, which is often accomplished using spatially invariant time trends that treat technologies as a mysterious, and uniformly improving, gift of time. We instead opted to directly measure the extent of uptake of four of the most important technological advances in corn production over the past century: irrigation, hybrid varieties, commercial nitrogen use, and adoption of genetically modified (GM) corn.

County-level irrigated acreage for corn is available in the various censuses starting in 1949, when only 0.6 percent of U.S. corn acres were irrigated. By 1959, about two percent of U.S. corn acres were irrigated, but with substantial variation among counties. At the high-end were the counties in the Pacific and Mountain regions, in which 91 percent and 63 percent of corn acres were irrigated, respectively (see USDA 1998, p.18 for a map of the regions). These regions irrigated the highest proportion of their corn acres in all years for which irrigation data were reported (followed by the Northern and Southern plains, which neither adopted irrigation as quickly nor as completely). Given the implied growth rates, it was assumed that no corn was irrigated prior to 1949, although it is recognized that the irrigation rate every year was actually slightly positive.

State-level hybrid corn adoption data are available from the USDA's Agricultural Statistics for 1933 through 1960. Of the 1,344 county and year observations, 218 were null and found at the beginning of each state's series when the initial uptake of hybrid varieties was negligible (Griliches 1957; Pardey et al. 2010). Almost all of the states had fully or nearly fully adopted hybrid varieties by 1960, although some states lagged significantly (for example, Arizona, with 42.5 percent adoption and Wyoming with 63.0 percent, although eventually, effectively full adoption occurred everywhere, see Dixon (1980)). These series were extended back to 1920 and forward to 2007 by assuming that the growth rates at the early end of each state's series extended backward to 1920, and that the growth rate around 1960 extended forward to 2007. Once a state achieved full adoption, it was assumed to stay at that level.

State-level data on nitrogen fertilizer use in corn are available from the USDA, ARS (1957) for 1954, from Ibach et al. (1964) for 1959 and from the USDA- ERS for the years spanning 1964-2010 (2011b). The state data are fairly sparse, and a number of values needed to be estimated. First, missing application rates for states were estimated from the data of other states using a weighted average where weights were the fourth power of the inverse distance between state centroids. Remaining null data points were then filled in by assuming that the growth rate in fertilizer use for any state was constant between any two periods for which data are available.

State -level data for the adoption of genetically modified corn are from the USDA-ERS from 2000 through 2010 (USDA-ERS 2011a). Proprietary data from Doane were used to calculate 1996-1999 adoption shares (see Pardey et al. 2010). These data cover the entire history of GM corn adoption, and GM adoption is taken to be zero in all states before 1996.

III. Econometric Methods

The benchmark model used to assess the effect of weather and intensification on corn yield was

(1) $Y_{it} = \beta_0 + \beta_W BWI_{it} + \beta_N FERT_{it} + \beta_{GM} GM_{it} + \beta_H HYBRID_{it} + \beta_I IRRIG_{it} + \varepsilon_{it}$

where Y_{it} is the corn yield in county *i* and year *t* measured in bu/ac; BWI_{it} is the bio-economic weather index; $FERT_{it}$ is the level of nitrogen fertilizer use in lbs/ac; GM_{it} is the percentage GM corn adoption; $HYBRID_{it}$ is the percentage hybrid corn adoption; $IRRIG_{it}$ is the percentage of irrigated corn acres; ε_{it} is a random error; and β_0, β_W, β_N, β_{GM}, β_H,and β_I are parameters to be estimated. Since farmers are likely to alter their fertility, seed, and irrigation decisions based on weather and climate, we also considered a specification that interacts the *BWI* with measures of intensification:

(2) $Y_{it} = \beta_0 + \beta_W BWI_{it} + \beta_N FERT_{it} + \beta_{GM} GM_{it} + \beta_H HYBRID_{it} + \beta_I IRRIG_{it}$

$+ \beta_{N\times W} FERT_{it}\times BWI_{it} + \beta_{GM\times W}\, GM_{it}\times BWI_{it} + \beta_{H\times W}\, HYBRID_{it}\times BWI_{it} + \beta_{I\times W}\, IRRIG_{it}\times BWI_{it} + \varepsilon_{it}$

with the additional estimable parameters $\beta_{N\times W}$, $\beta_{GM\times W}$, $\beta_{H\times W}$,and $\beta_{I\times W}$.

The weather index is constructed to capture the productivity enhancing aspects of weather as a natural input to production, so it is expected to be positively related to yield (e.g., $\beta_W > 0$). The use of fertilizer, improved hybrid seed, and irrigation at economically efficient levels is also expected to increase yield (e.g., $\beta_N > 0$, $\beta_H > 0$, and $\beta_I > 0$). GM crops like Bt corn provide improved insect control, which increases yield, though GM crops like herbicide tolerant corn either reduce production costs or increase yield, implying a yield increase is not necessarily expected. To the extent that the intensification of production substitutes for more suitable weather, measures of intensification interacted with the BWI in equation (2) are expected to be negatively related to yield (e.g., $\beta_{N\times W} < 0$, $\beta_{GM\times W} < 0$, $\beta_{H\times W} < 0$,and $\beta_{I\times W} < 0$), which is certainly the case for irrigation. Alternatively, if intensification complements favorable weather conditions, the interactions in equation (2) are expected to have a positive effect on yield (e.g., $\beta_{N\times W} > 0$, $\beta_{GM\times W} > 0$, $\beta_{H\times W} > 0$,and $\beta_{I\times W} > 0$). For the intensification variables other than irrigation, the effects of these interactions on yield are not obvious a priori.

Initially, equations (1) and (2) were estimated using ordinary least squares (OLS), though the interpretation of OLS results raises three particularly salient issues of concern: multicollinearity, spatial autocorrelation, and heteroscedasticity.[7] Multicollinearity is of concern because the adoption of improved seed, irrigation, and fertilizer in general may reflect a broader preference for intensification leading to high correlation and making parameter interpretations suspect. Subsequent variance inflation factor estimates for the bio-economic weather index and intensification variables however suggested multicollinearity was not likely a problem.

Spatial autocorrelation is of concern because neighboring counties are likely to have similar pest and disease pressure, production systems, and soil quality for example. Two common types of spatial autocorrelation are spatially lagged dependent variables and spatially lagged errors.[8] In the context of our analysis, spatially lagged dependent variables would imply that the yield in one county has a direct contemporaneous effect on the yield in a neighboring county. While such contemporaneous effects are plausible in terms of field level competition among densely planted corn for example, similar competition or other analogous effects seem implausible at a county level. Alternatively, spatially lagged errors would imply that there are some spatial processes impacting yield that are not adequately captured by our model (e.g., pest and disease impacts, soil quality, local management norms, crop and input prices, and use of farm machinery and implements). While it would be best to include information on these spatial processes directly into equations (1) and (2) to reduce spatial autocorrelation, acquiring the necessary long-run time series data was prohibitive.

The presence of spatially lagged errors can be explored using a variety of diagnostic tests. These tests require characterization of the suspected spatial relationships in the form of a spatial lag matrix—a $N \times N$ matrix of weights C_{ij} where N is the number of observations and C_{ij} reflects the "spatial influence" of observation j on observation i. For county-level, cross-sectional data in year t, a natural specification is $C_{ij}^t = 1$ if two different counties (i.e., $i \neq j$) share a border and $C_{ij}^t = 0$ otherwise. An issue that arises with operationalizing this specification is that we have an unbalanced panel—yields are not observed for every county in every year. Therefore, many counties in various years have no or only one bordering county making it more challenging to detect spatial autocorrelation if it exists.

An alternative is to suppose the kth nearest counties have a spatial influence, though it is likely that closer counties have a greater influence than more distant ones. To operationalize this notion, define d_{ij}

[7] Temporal autocorrelation was also considered as a potential concern, but was dismissed because the agricultural census data are only collected (at most) every five years.
[8] There are other types of spatial autocorrelation as well: spatially lagged explanatory variables and various combinations of spatially lagged dependent variables, independent variables, and errors.

for $i \neq j$ as the Euclidean distance between the centroids of counties i and j. Also, define N^t as the number of counties with observed yields at time t and Φ^t as the set of these counties. The distance between counties in Φ^t can be ranked such that $d_{ij(1)} \leq d_{ij(2)} \leq \cdots \leq d_{ij(N^t-1)}$ where $d_{ij(r)}$ is the Euclidean distance between the centroids of county i and the rth closest other county. The set $\Phi_k^t(i) = \{j(1), j(2),\ldots,j(k): i \in \Phi^t$ and $j(r) \in \Phi^t$ for $r = 1,2,\ldots,k\}$ is then just the set of k counties with yield observations in year t closest to the ith county with a yield observation in year t. This set can be used to define $C_{ij}^t = \begin{cases} d_{ij}{}^{-1}, & \text{if } j \in \Phi_k^t(i) \\ 0, & \text{otherwise} \end{cases}$ where the four nearest counties were chosen (i.e., k = 4). The convention is to row-normalize this spatial lag matrix such that $W_{ij}^t = \frac{C_{ij}^t}{\sum_{k=1}^{N^t} C_{ik}^t}$ yielding $\sum_{j=1}^{N^t} W_{ij}^t = 1$. The matrices $W^t = \begin{bmatrix} W_{11}^t & \cdots & W_{1N^t}^t \\ \vdots & \ddots & \vdots \\ W_{N^t1}^t & \cdots & W_{N^tN^t}^t \end{bmatrix}$ for t = 1,…, T are the spatial lag matrices for individual cross sections of data. It is straightforward to combine these into a single spatial lag matrix for the entire panel data set: $W = \begin{bmatrix} W^1 & \cdots & \mathbf{0}_{N^1N^T} \\ \vdots & \ddots & \vdots \\ \mathbf{0}_{N^TN^1} & \cdots & W^T \end{bmatrix}$ where $\mathbf{0}_{nm}$ is a n×m matrix of zeroes.

With the spatial weights matrix in-hand, it is now possible to examine whether the residuals of the regression are spatially correlated. A visual assessment can be made by plotting the standardized residuals against their spatial lag, as has been done in Figure 1. As the spatial weighting matrix has been constructed here, each point represents the error term of an observation on the horizontal axis, and the inverse distance weighted mean residual of that point's spatial neighbors on the vertical axis. Points in the first and third quadrants of the figure are either both above or below the average, and represent positive spatial autocorrelation. As the current dataset has over 60,000 points, only 5,000 randomly selected points are plotted in order to avoid visual clutter. A linear regression of the spatially lagged residuals on the residuals (e.g., $\varepsilon = \beta_0 + \beta_1\varepsilon$) was then fitted (using all of the observations), and the result is represented by the solid line. The positive slope of the line indicates that there is positive spatial autocorrelation in the data.

[Figure 1: Moran Scatterplot of Residuals]

The first formal diagnostic test we explored was a regression of the spatially lagged residuals from equation (1) or (2) on the residuals from equation (1) or (2). The results of these regressions were positive and statistically significant slope coefficients, which is indicative of positive spatial autocorrelation. The

Moran's I (Moran 1950) and Geary's C statistics calculated using the residuals for both models provided additional evidence that we could reject the hypothesis of no spatial autocorrelation at a one percent level of significance. Given this evidence, equations (1) and (2) were also estimated using a spatial errors model (SEM) with the assumption $\varepsilon = \lambda W\xi + \omega$ where ε is the vector of errors from equation (1) or (2), λ is an estimable parameter capturing the degree of spatial influence, ξ is a vector of independent standard normal errors, and ω is a vector of independent mean zero and variance σ^2 normal errors. The SEM model estimations used methods developed in Smirnov and Anselin (2009) and implemented using the R spdep package.

Heteroscedasticity is of concern because the absolute variation in crop yields tends to increase with an increase in mean yields. To test for heteroscedasticity in our estimates, we used a version of the Breusch-Pagan heteroscedasticity test that can account for spatial autocorrelation using the estimated λ — $\hat{\lambda}$ (Anselin 1988, pp. 121-123). Based on this test, we reject the null hypothesis of homoscedastic errors for both equations (1) and (2), so the estimated standard errors are inconsistent. White's heteroscedasticity-consistent standard errors can be used for both the OLS and SEM models to obtain robust standard errors. For the SEM model, the vector of residuals (ω) from the regression through the origin of Wy on $\hat{\lambda}WX$ (where y is the vector of yields) were used to calculate White's heteroscedasticity-consistent standard errors: $\left((\hat{\lambda}WX)'(\hat{\lambda}WX)\right)^{-1}(\hat{\lambda}WX)'diag(\omega)^2\hat{\lambda}WX\left((\hat{\lambda}WX)'(\hat{\lambda}WX)\right)^{-1}$.

IV. Results

Table 1 provides a descriptive summary of the data used in our estimations. Overall, the data include 60,079 county and year yield observations[9]. Average county yields increased more the fourfold from the period of 1889–1919 to 1982–2007 with more than a threefold increase in both the U.S. maximum and cross-county variability (as measured by the standard deviation). The bio-economic weather index (BWI) decreased from the period of 1889–1919 to 1924–1944, which reflects the severe droughts and "Dust Bowl" era of U.S. farming around the 1930s. After the 1924–1944 period, the U.S. average BWI increased. It is interesting to note that the cross-county variability of the BWI has decreased over time implying that the weather corn has been grown under has become increasingly homogenous, which is consistent with the increased spatial concentration in corn production over time in the central

[9] We begin with 23 years of data and 3,080 counties, or 67,760 observations. Removing observations with no yield leaves 60,079 observations.

and north central U.S. reported by Beddow and Pardey (2014). Fertilizer applications and hybrid corn adoption show similar increasing patterns over time, while also becoming less variable, which is again consistent with the increasing concentration of corn production over time and increasingly homogenous production systems. From 1982–2007, over a third of corn acres in a county were planted with GM varieties on average, a result that masks the rapid adoption that has taken place since commercialization in 1996—in 2007, 73 percent of U.S. corn acreage was planted with GM varieties (USDA-NASS 2008). Just under a third of county corn acres on average were irrigated from 1949-2007, with the average number of counties with irrigation increasing from the period of 1949–1978 (34.2 percent of the counties) to 1982-2007 (50.1 percent).

[Table 1: Summary of Variables]

The upper half of Figure 2, Panels a, b and c show, respectively, the actual corn production area-weighted average March, June and September temperatures (dashed line) and the counterfactual 1909 corn production area-weighted average temperatures (solid line) over time. Thus, the extent to which the solid line is above the dashed line shows how much changes in spatial movement and concentration of corn production since 1909 has resulted in a decrease in average growing temperatures, as quantified by the lower half of each of the panels. Depending on the year, the spatial movement of corn production resulted in a 3-4^{o}C drop in average March growing temperatures, a 1-1.25^{o}C drop in June temperatures, and a nearly 2^{o}C drop in September temperatures, which suggests that spatial movement has potentially reduced the effects of climate change (or at least any generalized warming in climate) on corn production. Given that corn yields have increased over time, it is also easy to conclude that the changing footprint of production has resulted in more suitable weather for corn production, but such a conclusion is confounded by the intensification of production and other spatially variable factors that have also changed during this time period.

[Figure 2: Average temperature changes due to spatial movement, 1889-2007]

The top panel of Figure 3 shows the average BWI values for each year, weighted by the actual (solid line) and counterfactual 1909 (dashed line) corn production-areas. The bottom panel shows the difference in actual and counterfactual average BWI where positive values indicate that the actual crop area was more suitable for corn development than the 1909 area. While the indexes are positively correlated, the actual BWI is almost always higher than the counterfactual. By this metric, the spatial movement of corn production over the past century has indeed improved corn growing conditions, highlighting the importance of considering location, and changes in location, when assessing productivity. It is interesting to note that the differences in the bottom panel are positive with the exception of three years: 1909 which is zero by design, and 1924 and 1929 when the counterfactual BWI was slightly higher. The census years 1969 and 1978 are particularly evident in the bottom panel of the figure. Both years saw better than average weather for producing corn (as indicated by the average BWI) for the actual and counterfactual areas. However, the actual area exhibited average BWI values that were about 40 percent above the long-run mean, while the counterfactual area had average BWI values that were only about 15 percent higher than normal.

[Figure 3: Bio-economic weather index, 1889-2007]

The effect of weather and intensification on corn yield is seen in the OLS and SEM parameter estimates for equation (1) reported in Table 2. All mean parameter estimates for both models are positive and statistically significant at one percent. For the SEM model, $\hat{\lambda}$ is positive and statistically significant at one percent, providing further evidence of spatial autocorrelation. Accounting for this autocorrelation decreased the parameter estimate for fertilizer by about a quarter and increased the estimate for hybrid adoption by over 75 percent. The other intensification parameter estimates are of similar magnitude in the two models. The BWI parameter changed only modestly.

[Table 2: OLS and SEM Results without Interactions]

These results suggest that our BWI has the ability to account for the effect of weather on corn yields. Namely, when all of the management cum intensification variables are zero, as would be the case in the earlier years, yields would range from about 10 to 40 bushels per acre. In the period before 1910, the mean area-weighted BWI value was 0.579, implying that the mean yield of about 26.0 bushels per acre; the actual area weighted mean yield for that period was 27.6 bushels per acre. Since all of the intensification variables have positive coefficient estimates, as adoption and use of improved varieties, fertilizer and irrigation increased over time, the *relative* importance of weather decreased. This concords with Schultz's (1951) finding of the still significant, but declining, economic importance of agricultural land; not only because the agricultural share of economic output has declined, but also because "…the value added by land … declined relative to all inputs used in farming (p. 735)."

OLS and SEM parameter estimates and standard errors for equation (2) are reported in Table 3. Again, all of the mean parameters are significant at one percent as is $\hat{\lambda}$. They are also all positive with the exception of the interaction between the BWI and irrigation. These results suggest that more suitable weather complements the use of fertilizer and adoption of hybrids and GM seed in terms of increased yields. Intuitively, more suitable weather is a substitute for irrigation.

[Table 3: OLS and SEM Results with Interactions]

Comparing the SEM models with and without the BWI and intensification interactions, the pseudo-R^2 is modestly larger and $\hat{\lambda}$ modestly smaller with the interactions included. With the interactions, the direct effect of the BWI is reduced, so that an increase in the index of 0.1 points will, on average, be expected to increase yields by 1.45 bushels per acre. Remarkably, full adoption of irrigation is estimated to increase the yield of a county by about 55 bushels per acre, but this effect is almost entirely cancelled out with perfect weather (BWI = 1)—a surprisingly accurate result, considering that a BWI equal to one can only be achieved if the soil moisture index equals one for all phenological stages.

To explore our results further, consider three crop management regimes, representing the average technology adoption and use of 1899-1909, 1959-1969 and 1997-2007 (Table 4). Under the 1899-1909 scenario, the marginal effect of the BWI is 14.5 bushels per acre, or 54 percent of average yield. As production intensifies, the relative marginal effect of weather decreases, such that in the 1997-2007 scenario, the marginal effect is 39 percent of average yield (53.7 bushels per acre). Alternatively, consider three weather scenarios: a poor weather year (BWI = 0.1), a moderate weather year (BWI = 0.5) and a good weather year (BWI = 1.0). The expected yield under each intensification scenario is presented in the left portion of Table 4. Based on these results, a good weather year under the 1899-1909 scenario increases yield by about 80 percent over the expected yield under poor weather, while a good weather year increases the yield in intensively managed areas (typified by the 1997-2007 scenario) by about 54 percent. The expected yields under the poor, moderate and good weather scenarios roughly correspond to the first, second and third quartiles of the yield distributions of the respective periods (right part of Table 4), indicating that the expected yield for each period is within reason.

[Table 4: Expected Yield and Yield Quartiles]

V. Conclusions and Implications

We developed a long-run, intra-seasonally dynamic and location-specific “bio-economic weather index” (BWI) to use in assessing the spatial and temporal effects of weather and intensification on U.S. corn yields over more than a century. By construction, our BWI endogenizes farmer choices concerning the location of production over time and the timing of planting operations (and thus subsequent crop growth) within each season, with significant and hitherto unmeasured consequences for the pattern of weather that actually affects the crop. By integrating complex non-additive and non-linear interactions between weather, biology, and farmer behavior, the BWI is constructed to have a monotonic increasing relationship with corn yields. This increasing monotonic relationship implies it is consistent with the ubiquitous free disposal assumption in production theory, so it can be thought of like any other productive input. Therefore, we can use this theory to interpret and judge the sensibility of observed relationships between weather and other productive inputs, contrary to much of the previous literature that has treated weather more as a statistical nuisance by deploying a variety of weather variables, while searching for combinations that provide the best statistical fit.

Using a long-run panel data set of U.S. county yields, we are able to confirm a monotonic increasing relationship between more suitable weather as measured by the BWI and corn yields. We also found that more suitable weather complements intensification in terms of nitrogen fertilizer adoption and use, and the adoption of hybrid and genetically modified seed. Alternatively and quite intuitively, more suitable weather is found to substitute for irrigation—indeed, we find that exceptionally favorable weather almost completely nullifies the benefits of irrigation. Most importantly however, having endogenized farmer crop planting behavior by way of construction of the BWI, we found that over the past century the relative economic importance of more suitable weather for yields has fallen with the intensification of production, in tandem with the declining economic importance of another important natural input, agricultural land (Schultz 1951).

The common use of time trends in the literature to proxy for technical change and the intensification of agriculture can be useful for developing long-run projections of future productivity growth. They are less useful for evaluating the potential for technology adoption and intensification to boost production in regions of the world where crops are currently gown in less hospitable climates with few inputs other than land and labor. By substituting explicit temporal and spatial measures of technology adoption and intensification for time trends in a long-run analysis of yield growth that incorporates the temporal and spatial variability of weather, the results of our analysis capture the effects of both low and high levels of intensification, as well as good and bad weather on corn yields. Thus, our results can provide new insights into how transforming the world's low-input corn production systems into higher-input systems and moving these systems to more hospitable climatic regions might boost global corn productivity.

For example, applying the BWI methodology to data pertaining to sub-Saharan African corn production (FAO 2013) suggests it is currently produced under conditions similar to those experienced during the U.S. Dust Bowl period. If sub-Saharan Africa experiences an output-improving spatial reallocation in corn production that improves its BWI to that of the United States, corn output could be increased by about 30 percent at its current level of intensification. Alternatively, sub-Saharan Africa corn production systems are well behind the United States in intensification. Adoption of improved corn varieties (including modern open-pollinated varieties) varies across sub-Saharan African countries, but is generally between 44 and 60 percent. Fertilizer use in corn averages about 15 pounds per acre (Smale et al. 2011). GM varieties occupied about six percent of sub-Saharan African corn area in 2010,[10] and 5.5 percent of the corn area was irrigated.[11] Our results suggest that sub-Saharan Africa could increase its average yields by about 170 percent, equivalent to 60 percent of current U.S. average yields, by increasing improved seed, nitrogen fertilizer, and irrigation adoption to current (1997–2007) U.S. levels even without relocating current production.

Previous efforts to explore the consequences of climate change on U.S. agricultural productivity have typically ignored the changing footprint of agriculture or relied on confounded proxies like land rents to circumvent the issue. The methodology we use to construct the BWI provides an alternative. By developing BWIs for a host of important crops and establishing the relationships between these BWIs and yields, it becomes possible to forecast comparative yield advantages over time and space in terms of weather. Such forecasts are necessary for developing more structural models that can be used to explore how climate change will affect the footprint of agricultural production and agricultural productivity more generally and in ways that endogenize important cropping decisions about what to plant, where and when.

[10] This value was calculated based on data presented by James (2010), assuming that South Africa was the only sub-Saharan African country to have adopted GM corn. Regulatory approval for GM corn is spreading throughout sub-Saharan Africa, and as of 2010, Kenya and Uganda had approved its use, although it had not yet been commercialized.

[11] Based on calculations by the authors using the HarvestChoice SpAM data (You et al. 2011).

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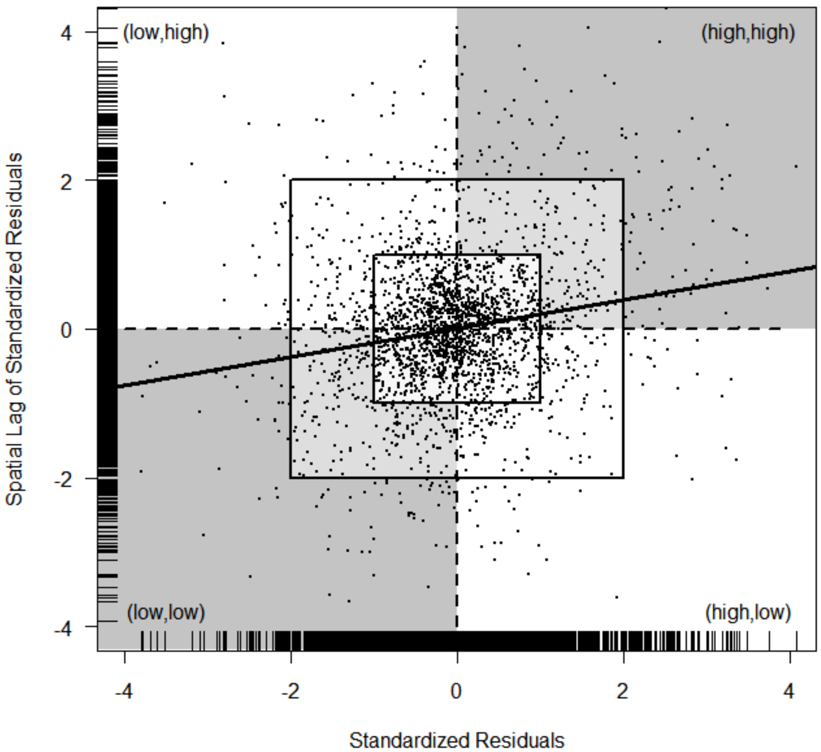
FIGURE 1: MORAN SCATTERPLOT OF RESIDUALS

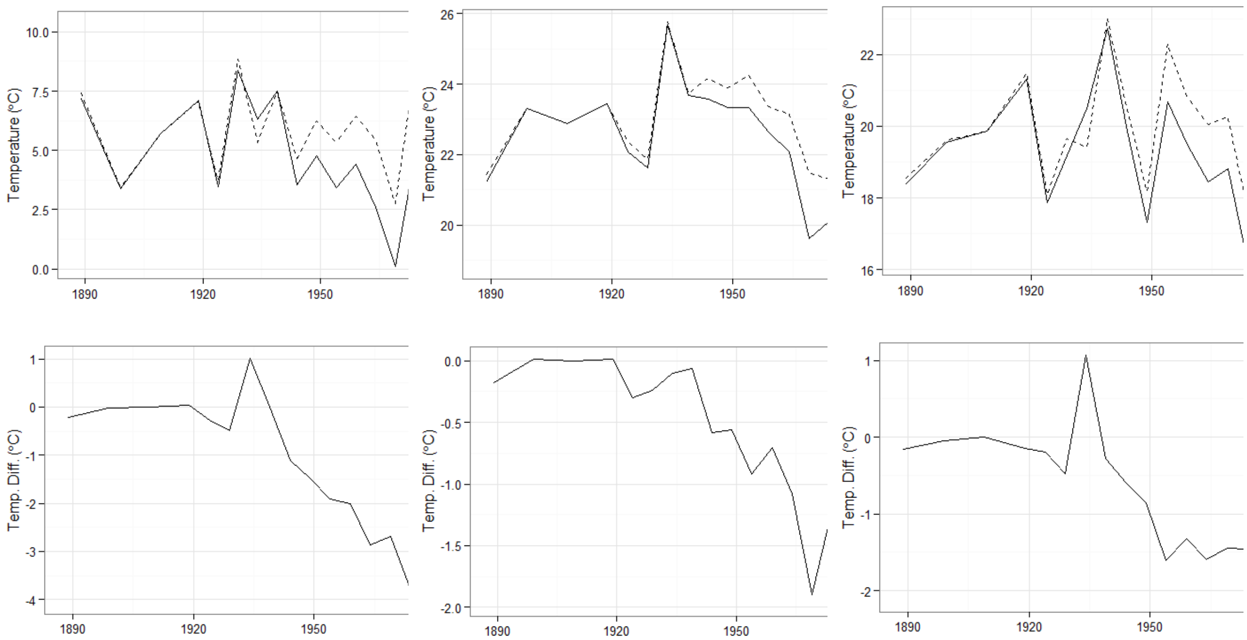


Source: The general form of this figure was suggested by Ward and Gleditsch (2008). The values were calculated using the data described in Table 1.

Notes: This figure summarizes the standardized residuals from the SEM regression. To avoid over-plotting, only 5,000 randomly selected residuals are shown (of the over 60,000 available data points). The line represents a simple regression (through the origin) of the spatially lagged residual on the residual. The "rug" on each axis represents the point density in that dimension. The slope of the line was 0.178 (standard error = 0.004).

FIGURE 2: AVERAGE TEMPERATURE CHANGES DUE TO SPATIAL MOVEMENT, 1889-2007

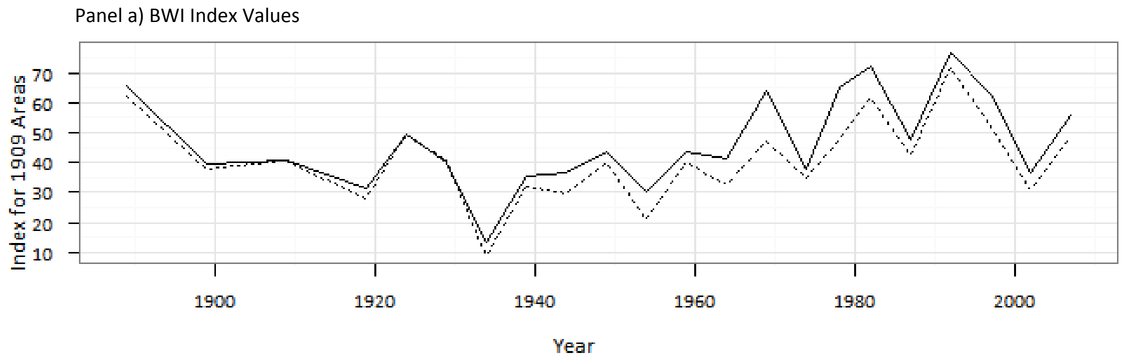
Panel a: March Panel b: June Panel c: September

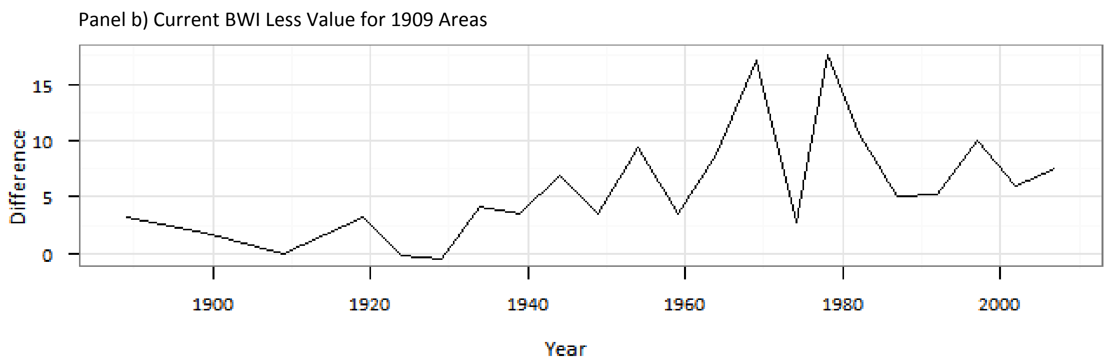


Source: Derived using the data described in Beddow (2014.

Notes: The top chart in each panel shows the average temperature for the 1909 area (solid line) and the current-year area (dashed line). The bottom chart in each panel shows the absolute temperature difference between the 1909 corn area and the current-year corn area

FIGURE 3: BIO-ECONOMIC WEATHER INDEX, 1889-2007





Source: Derived using the data described in Beddow (2014).

Notes: The top panel shows the area-weighted BWI values for the current corn harvested area (solid line) and for the 1909 area (dashed line), always calculated using the current year's weather. The bottom panel represents the increase in the weighted average BWI values due to the spatial reallocation of corn area that occurred between 1909 and current year.

TABLE 1: SUMMARY OF VARIABLES

Variable		Period	N	T	Zeros	Min	Q1	Q2	Q3	Max	Mean	Sd
						Summary of Non-Zero Entries						
Yield	(bu/ac)	1889-1919	11,942	4	0	1.5	14.8	22.1	31.3	79.4	23.8	10.9
		1924-1944	14,676	5	0	0.7	13.0	20.4	30.5	76.1	22.5	12.1
		1949-1978	19,539	7	0	2.0	28.3	45.8	66.8	178.5	49.1	26.2
		1982-2007	13,922	6	0	2.0	76.8	98.6	122.2	254.4	100.2	33.8
		1889-2007	60,079	22	0	0.7	20.0	36.2	72.1	254.4	49.4	38.1
BWI	(0-1)	1889-1919	11,942	4	83	0.00	0.10	0.42	0.70	1.00	0.42	0.32
		1924-1944	14,676	5	260	0.00	0.02	0.23	0.63	1.00	0.33	0.31
		1949-1978	19,539	7	189	0.00	0.15	0.42	0.66	1.00	0.42	0.30
		1982-2007	13,922	6	34	0.00	0.32	0.54	0.74	1.00	0.53	0.27
		1889-2007	60,079	22	566	0.00	0.13	0.42	0.68	1.00	0.43	0.31
Nitrogen Application	(lb/ac)	1889-1919	11,942	4	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		1924-1944	14,676	5	0	0.0	0.1	0.2	0.8	5.7	0.7	0.9
		1949-1978	19,539	7	0	0.2	14.4	56.9	103.0	158.4	60.7	46.4
		1978-2007	13,922	6	0	47.6	125.9	136.8	146.1	163.4	132.5	20.5
		1889-2007	60,079	22	0	0.0	0.1	10.0	117.8	163.4	50.6	59.2
GMO Adoption	(pct. of acres)	1889-1919	11,942	4	11,942							
		1924-1944	14,676	5	14,676							
		1949-1978	19,539	7	19,539							
		1982-2007	13,922	6	7,068	0.5	9.0	32.7	69.3	93.0	37.7	27.3
		1889-2007	60,079	22	53,225	0.5	9.0	32.7	69.3	93.0	37.7	27.3
Hybrid Adoption	(pct. of acres)	1889-1919	11,942	4	11,942							
		1924-1944	14,676	5	0	0.1	0.1	0.3	4.0	99.8	10.7	23.8
		1949-1978	19,539	7	0	3.5	89.0	99.5	100.0	100.0	89.7	19.5
		1982-2007	13,922	6	0	100.0	100.0	100.0	100.0	100.0	100.0	0.0
		1889-2007	60,079	22	11,942	0.1	10.0	99.5	100.0	100.0	68.6	42.6
Irrigation	(pct. of acres)	1889-1919	11,942	4	11,942							
		1924-1944	14,676	5	14,676							
		1949-1978	19,539	7	12,849	0.0	0.4	3.8	69.1	100.0	29.8	39.5
		1982-2007	13,922	6	6,952	0.0	1.8	8.9	59.2	100.0	30.1	36.8
		1889-2007	60,079	22	46,419	0.0	0.9	6.6	63.5	100.0	29.9	38.1

Source: The data sources of the variables are described in Beddow (2014).

Notes: Summary statistics are shown for non-zero entries only. The minimum may appear to equal zero due to rounding. Nitrogen application never equals zero, although the application rate approaches zero according to the estimated adoption curve.

TABLE 2: OLS AND SEM RESULTS WITHOUT INTERACTIONS

Variable	OLS			SEM		
	$\hat{\beta}$	$SE(\hat{\beta})$	t Value	$\hat{\beta}$	$SE(\hat{\beta})$	z Value
Intercept	10.840	0.158	68.710	10.412	0.219	47.649
BWI	28.420	0.270	105.450	26.951	0.267	101.070
NITRO	0.319	0.002	133.000	0.241	0.003	76.894
GMO	0.512	0.006	86.680	0.537	0.009	58.218
HYBRID	0.116	0.003	40.540	0.206	0.004	54.318
IRRIG	0.270	0.004	70.310	0.269	0.004	73.061
λ				0.407	0.008	49.677
df		60,073			60,073	
R^2		0.728			0.739	
Log likelihood		-264,882			-263,261	

Notes: The R^2 for the SEM is the Nagelkerke R^2. To maintain scaling of the results, *BWI* is a decimal percent, with a potential range of zero to one.

TABLE 3: OLS AND SEM RESULTS WITH INTERACTIONS

Variable	OLS			SEM		
	$\hat{\beta}$	$SE(\hat{\beta})$	t Value	$\hat{\beta}$	$SE(\hat{\beta})$	z Value
Intercept	15.87	0.18	87.3	14.97	0.11	130.8
BWI	14.73	0.38	39.1	14.50	0.20	72.1
NITRO	0.25	0.00	55.8	0.19	0.01	35.2
GMO	0.47	0.01	40.6	0.47	0.02	20.6
HYBRID	0.03	0.01	6.0	0.11	0.00	27.7
IRRIG	0.55	0.01	78.2	0.56	0.01	49.0
BWI*NITRO	0.13	0.01	15.7	0.10	0.01	11.2
BWI*GMO	0.15	0.02	6.8	0.19	0.04	5.1
BWI*HYBRID	0.24	0.01	25.6	0.23	0.01	31.5
BWI*IRRIG	-0.54	0.01	-47.5	-0.54	0.02	-29.6
λ				0.39	0.01	47.2
R^2		0.73			0.76	
Log likelihood		-262,374			-261,262	

Notes: The R2 for the SEM is the Nagelkerke R2, and the standard errors are adjusted for heteroskedasticity. To maintain readability of the results, BWI is a decimal percent, with a potential range of zero to one (without this correction, the parameters on the interacted terms become very small).

TABLE 4: EXPECTED YIELD AND YIELD QUARTILES

Expected Yield				Yield Quartiles			
	Management Scenario				Period		
Weather	1899-1909	1959-1969	1997-2007	Quartile	1899-1909	1959-1969	1997-2007
		bu/ac				*bu/ac*	
Poor	16.4	31.8	83.9	First	14.9	23.9	81.6
Moderate	22.2	46.1	104.2	Second	22.1	38.2	105.3
Good	29.5	64.0	129.5	Third	31.1	54.7	130.9

Notes: Poor, Moderate and Good weather scenarios were calculated using a BWI of 0.1, 0.5 and 1.0, respectively. The technology adoption scenarios represent the area-weighted average technology adoption and use for the indicated periods.