Reclaiming soils to sustain maize and soybean productivity in the Midwestern US given climate change

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Abstract: I build a model that explains Midwestern US maize and soybean yield as a function of weather and soil capability. Climate change is expected to reduce mid-century maize and soybean yields in the Midwest by 8% to 28% and 7% to 23%, respectively, depending on cropped land's soil capability and severity of climate change, compared to baseline values calculated with no climate change. I find that small improvements in the capabilities of the most marginal cropped soils can completely reverse the predicted yield losses due to climate change. Further, small investments in the reclamation of the Midwest's least capable cropped soils would greatly reduce the risk of low yield outcomes under the future Midwestern climate. While I demonstrate that investments in soil reclamation on the least capable Midwestern soils can enhance social welfare under expected climate change (assuming reclamation costs are reasonable), economists will need to work closely with agronomists to identify where and what types of reclamation projects would generate most cost-effective returns in the Midwest under climate change.

Keywords: soil reclamation, crop productivity, climate change

JEL Codes: Q01, Q10, Q24, Q54, Q57

The summer of 2012 demonstrated how sensitive crop production in is to weather. Widespread drought in the Midwestern US reduced maize and soybean yields in the US's breadbasket to levels not seen on a regular basis since the early to mid-1980s (USDA-NASS 2013). According to climatologists summers like 2012 will become much more routine in the Midwest's future. Besides the greater variation in weather, climatologists also predict warmer growing season temperatures in the region's future (Kunkel et al. 2013).

We can expect Midwestern farmers and agricultural institutions to implement various measures to reduce the negative impact that greater weather variability and warmer growing season months will have on maize and soybean yields (Schlenker and Roberts 2009, Smith and Olesen 2010, Moriondo et al. 2010). Some of these adaptations will be made possible by innovations in biotechnology and crop science (e.g., Royal Society 2009). Reclamation of the region's least capable cropland soils is another way to maintain or improve the area's agricultural productivity in the face of climate change (Hatfield et al. 2008, Backlund et al. 2012). According to USDA-NRCS (2012) the capability of cropland soils can be improved by establishing major drainage facilities, building levees or flood-retarding structures, providing water for irrigation, removing stones, large-scale grading of gullied land, and other projects that permanently change the soil's limitations.

In this article I estimate the impact of soil reclamation projects on expected 2050-2058 maize and soybean yields and net revenues in the Midwest under several scenarios of climate change. First, assuming no changes in Midwestern soil capability, I find that, on average, climate change will reduce mid-21st century maize and soybean yields in the Midwest by 8% to 28% and 7% to 23%, respectively, depending on cropped land's soil capability and severity of climate change, compared to baseline values calculated with no climate change. Second, I find that small investments in cropland soil's capability can ameliorate some of these expected losses, and in some cases, completely reverse the predicted yield losses due to climate change. In monetary terms I estimate that relatively minor soil reclamation on the representative maize field with the least capable soils would mean an additional $45 (2000 USD) of net returns per acre per year by 2050-2058 assuming 2000-2008 commodity prices and production costs (not including the private amortized costs of soil reclamation; USDA-ERS 2013). And on a representative soybean field with the least capable soils relatively minor soil reclamation is expected to produce an extra $27 (2000 USD) of net returns per acre per year assuming 2000-2008 commodity prices and production costs (not including the private amortized costs of marginal soil reclamation; USDA-ERS 2013). Given that the average net return to an acre of maize and soybeans was $95 and $178 (2000 $), respectively, in the Midwest from 2000-2008, additional returns from small investments in soil reclamation could be non-trivial. I also find small investments in soil reclamation can greatly reduce the likelihood of a very low yield outcomes; a benefit that risk adverse farmers may value even more highly than an increase in expected returns given the rapidly increasing variability in growing season weather. In short, my research shows that investments in soil reclamation on the least capable Midwestern soils could be part of a portfolio of cost-effective adaptive measures to expected climate change.

One of global society's greatest 21st century challenges will be to find a way to meet a growing global population's demand for food while minimizing the rate of agricultural-driven environmental degradation (e.g., Foley et al. 2011). However, the imperative of the first goal will mean that the latter preference is likely to be sacrificed *unless* we become much better at utilizing the cropped soils we already use. Investing in the reclamation of the more marginal cropped soils is one way to make our already cropped land more productive. Surprisingly, the strategy of improving soil resources to help meet the increasing global demand for food while minimizing the impact of agricultural production on the environment has received little attention in the recent literature on the challenges facing 21st century global agriculture. For example, recent prominent papers on how to enhance agricultural productivity around the world at least cost to the environment have focused on using fertilizers and irrigation water more strategically and eliminating policies that promote food as biofuel feedstock but have said next to nothing on improving cropland soil capabilities (e.g., Foley et al. 2011, Tillman et al. 2011, Mueller et al. 2012). I believe that ignoring the role that soil reclamation can play in meeting future agricultural challenges is a glaring omission given my results. Hopefully this paper will focus additional research and policy attention on this complementary adaptation strategy of cropland soil improvement.

In the next section I explore the historical relationship between weather, soil capability, time, and maize and soybean yields in the Midwest US. Next I describe the statistical model that I use to relate maize and soybean yields in the Midwest to growing season weather, cropland soil capabilities, and temporal trends in crop productivity. Then I explain how I measure the expected impact that small investments in soil capability can have on maize and soybean yield and monetary returns. Finally, I predict the impact that marginal soil capability improvements could have on crop yields in the Midwest by the middle of the 21st century given climate change.

Long-term trends in maize and soybean yields in the Midwest

I focus on maize and soybeans because they have become the most important Midwestern crops both in terms of area planted and value. For example, by 2007, 38% of the region's harvested cropland was in maize for grain and 27% in soybeans. Further, 50% of the region's crop revenue in 2007 was derived from maize for grain and 26% from soybeans (USDA-NASS 2009). Therefore, determining ways to safeguard the productivity of these two crops in the face of climate change will be vital to the health of the Midwestern agricultural economy and necessary to keep maize and soybean-based food and animal feed affordable throughout the world (Parry et al. 2007).

Although there are twelve Midwestern states, I restrict my analysis to six, Illinois, Indiana, Iowa, Michigan, Minnesota, and Ohio, primarily to limit the size of the database and to avoid the complicating factor of irrigation.[i] Irrigation use, because it can substitute for insufficient precipitation, can obfuscate the impact of weather on crop yields unless the modeler can properly control for its use (Schlenker et al. 2006). Unfortunately, data on annual irrigation use across different crops has only recently been systematically cataloged by the USDA and this study includes yield data from as far back as 1950. To avoid this omitted variable problem I only include Midwestern states where irrigation is rarely used to produce maize and soybeans. For example, in 2007 the six states included in this study only irrigated 2.6% of their maize for grain acres and 1.07% of their soybean acres. The Midwestern states not included irrigated 31.10% of their maize for grain acres and 12.19% of their soybean acres (USDA-NASS 2009). Other then the irrigation differences, there is every other reason to believe that these six states are collectively representative of the Midwest. There are no unique soil capability patterns and management styles in the omitted states and over time all states included in this study have had growing seasons typically experienced by the omitted states. Finally, the six states I have chosen produce the bulk of the region's maize and soybeans (USDA-NASS 2009).[ii]

Using data from USDA-NASS (2013), I create a 1950 to 2008 dataset with annual county-level area planted and harvested and average yields for maize for grain and soybeans across six Midwest states where c indexes counties and $j = m$ or s indexes maize for grain or soybeans, respectively. Let average county-level yield of crop j in county c in year t be given by Y_{jct}. Let A_{jct} indicate the percentage of county area used to harvest crop j in county c in year t. To this crop production dataset I append county-level growing degree day (*GDD*) and growing season precipitation (*PRECIP*; measured in mm) values for maize for grain and soybean production for the years 1950 to 2008. I calculate county-level *GDD* and *PRECIP* for each crop j and each year t using gridded maps of average monthly weather data (CRU 2010) and typical planting and harvesting dates for each crop (Sacks et al. 2010). When calculating *GDD* and *PRECIP* I assume planting and harvesting dates remained static from 1950 to 2008 (see Appendix Text A for more information of the calculation of GDD_{jct} and $PRECIP_{jct}$).

Next I calculate a time-invariant soil capability score for each county c, given by L_c. County c's soil capability score is higher if c's soil profile has a greater density of more capable soils (Radeloff et al. 2012). Then I divide the study area's counties into 5 groups (quintiles) according to ranked L_c scores. The 20% of counties with the greatest density of capable soils as measured by the soil statistic L_c are grouped together in the set labeled S_5, the 20% of counties with the next most capable soils are grouped together in the set labeled S_4, etc. Let $q = 1,\ldots,5$ index the soil capability classes in ascending order of capability. I use soil capability bins because I want to jointly model the effect of soil capability *and* county-level fixed effects on yield; if I used each county's time-invariant L_c score to describe its soil resources I could not fix the overall county effect on yield. (See the Appendix Text B for more information on the calculation of L_c and the creation of the sets S_q.)

Before building a model that explains maize and soybean yield as a function of weather, soil capability, and time I present evidence that historical county-level maize and soybean yields in the Midwest are correlated with my summary statistics of county-level growing season weather and soil capability in expected ways. In figure 1 I plot the GDD_{mct} and $PRECIP_{mct}$ values for the ten highest and ten lowest Y_{mct} for each $\{S_q; t\}$ combination. I separate the data by decade in order to visualize any trends over time. The figure suggests that maize production has a GDD "sweet spot" (indicated by the gray boxes in each decadal subplot) that has generally grown larger over time, accommodating both cooler and warmer than normal growing seasons. However, despite showing greater capacity to deal with abnormal weather, very low and very high GDD_{mct} is still associated with sub-par yields (e.g., Lobell and Asner 2003, Schlenker and Roberts 2009). Finally, figure 1 indicates that GDD_{mct} appears to be more limiting than $PRECIP_{mct}$ when it comes to crop performance: low and high precipitation levels both were associated with high performance. The highest and lowest county-level soybeans yields display a similar relationship with GDD_{sct} and $PRECIP_{sct}$ (see Appendix Text C for a soybean version of figure 1).

Further evidence that the county-level weather and soil capability variables I have constructed are good approximations of historical agronomic conditions in the Midwest comes from the estimated correlation between county-level weather, soil capability, and the percentage of planted maize and soybean harvested in a county. A planted crop is less likely to be harvested, or in the case of maize, harvested for grain (stunted maize unsuitable for grain can be used for silage) if its growing season includes one or more incidences of extreme weather (Weiss 2007, Hatfield et al. 2008, Thomas 2012). At the same time, crops on more capable soils should be more resilient to extreme weather that could lead to crop failure, all else equal (a soil's capability score is partly based on the risk of a crop failing on it). To test that my dataset corroborates these intuitive notions I estimate a model of county-level crop failure rates from

1950 to 2008 that are explained by the weather and soil capability class variables in my datatset. As expected, I find that very low or high *GDD* and *PRECIP* (extreme weather incidences during the growing season will tend to drive *GDD* and *PRECIP* much lower or higher than normal) and declining soil capability increase the rates of maize and soybean failure in a county (see Appendix Text D for detailed estimation results).

Finally, the averages of county-level yields by soil capability class are consistent with intuition: as S_q increases the average of annual county-level yields across the entire time frame improve and relative variability in yields decreases (see Appendix Text E). Therefore, to summarize, the biophysical dataset I have created to describe agronomic conditions across the Midwest over time is correlated with yield outcomes in expected ways.

Explaining Midwest maize and soybean yields as a function of weather, soil capability, and time

For the set of counties in set S_q I regress crop *j*'s yield in county *c* in year *t* on time, county *c*'s growing season weather for crop *j* in year *t*, and the distribution of land use in county *c* in year *t*,

$$Y_{jct} = \delta_c + \gamma_{0j} + \gamma_{1j}t + \gamma_{2j}t^2 + \gamma_{3j}GDD_{jct} + \gamma_{4j}GDD_{jct}^2 + \gamma_{5j}PRECIP_{jct} + \gamma_{6j}PRECIP_{jct}^2 + \gamma_{7j}A_{jct} + \gamma_{8j}A_{-jct} + \gamma_{9j}A_{wct} \quad (1)$$

where the coefficient δ_c fixes the effect of county *c*'s unique time-invariant unobserved variables (biophysical, economic, managerial, political, and cultural) on its yield of *j* across time, A_{wct} indicates the percentage of the county's area used for winter and spring wheat harvest in year *t*, the index –*j* indicates the other modeled crop (soybeans or maize), and all other variables are as before. While I also assume that soil capabilities in each county were fixed from 1950 to 2008 but I am able to identify the impact of soil capability on yields by estimating (1) for groups of counties with similar soil capabilities and comparing estimated results across soil groups (see the 'Robustness Checks' section for evidence that my assumption of fixed soil capabilities is not problematic even though *some* counties may have changed their soil's capability enough to warrant membership in another soil capability group).

In this model time is a proxy for productivity growth in maize and soybeans driven by technology and managerial know-how. I include the quadratic term for year in the model to account for any non-linear productivity or 'trend yield growth' trajectories (Lobell and Asner 2003) for each $\{S_q, j\}$ combination. To capture the non-linear impact growing season weather can have on crop growth, I include squared terms of GDD_{jct} and $PRECIP_{jct}$ model (1) (Schlenker and Roberts 2009). I include a variable for winter and spring wheat area because it was the 3rd most harvested crop in this six state region over the 1950-2008 time frame. The percentage of land in all other uses in county *c* in year *t*, given by $100 - A_{jct} - A_{-jct} - A_{wct}$, is omitted from (1) to avoid perfect multicollinearity (see Appendix Text E for on the land use allocation variables).

I use the land use allocation variables in an attempt to overcome a modeling shortcoming associated with using county-level data. If I could combine field-level maps of annual maize and soybean production with the already existing field-level soil maps then my yield model much more accurate as I could create sets of *fields* with similar soil capabilities rather than sets of counties with similar soil capabilities. However, field-level crop maps for the Midwest have only been published since the late 1990s and therefore I am forced to use county-level areal measures of crop production. This data limitation requires me to generally assume that a county's overall distribution of soil capabilities matches the distribution of soil capabilities used to produce j. This assumption is generally not problematic for counties with larger A_{jct}; as the variable approaches 1 it is more and more likely that the soil profile used to generate j in c at time t is well described by the county's soil capability summary statistic L_c. However, fro counties with lower A_{jct} values it is increasingly likely that j's production occupies a soil space in c that is not representative of c's soil capability class (although the previously reported finding, that as S_q increases the average and variance of county-level yields has improved and decreased, respectively, from 1950-2008, indicates that the incidences of class misrepresentation are infrequent even in the most lowest soil capability classes). Further, in counties where A_{jct} is low, marginal expansion or contraction in j's harvested area over time has a greater capacity to alter the relative mix of soil capabilities used to grow j than in counties where A_{jct} is consistently high. Therefore, by including area variables in the model I potentially control for the effect marginal changes in the relative mix of soil capabilities used to grow j can have on the county-level yield of j, especially in counties with lower A_{jct} values.

The entire set of estimates of model (1) for all $\{S_q; j\}$ combinations are given in Appendix Text G. Here I discus the highlights. For maize specifically, county-level yields exhibit the expected inverted U-shape response to growing season weather across all soil capability classes. Warmer and/or wetter growing seasons have a positive impact on yield up to a point; eventually too much warmth and wetness begins to drag yield down. Further, as expected, county-level maize yields in all soil capability classes have increased over time, all else equal, due to innovations in technology and management (Duvick 2005). However, maize 'trend yield growth' has not progressed equally across soil capability categories. Trend yield growth has been decelerating across S_1 counties since 1950 and accelerating in all other classes.

Further, the greatest acceleration rates are currently found in S_3 and S_4 counties; up to 1990 S_5 counties displayed the greatest acceleration in trend yield growth (see the Appendix Text H for a graph of trend yield growth trajectories by capability class).

Counties with high levels of cropped area also tend to have the most capable soils. Therefore, when I find the effects of the crop area variables on maize yield are smaller across S_4 and S_5 counties I am finding that slight changes in areal distribution of crops has had little effect on county-level maize yields in counties with significant maize, soybean, and wheat acreage. In other words, in higher soil classes the profile of soils used to grow maize is relatively stable over time. In contrast, larger estimated coefficients on A_{mct} in the S_1 and S_2 groups (areas less devoted to maize, soybean, and wheat production in general) indicates that the profile of soils used for maize production in these areas is more malleable over time. Specifically, I deduce that maize for grain tends to use the better soils in S_1 and S_2 counties as its footprint expands in these counties. Further, the use of the upper tail of a county's soil capability profile in the lower capability class counties appears to be, at least historically, a competition between maize and wheat production. As wheat area in S_1 counties has gone up, presumably supplanting some maize area, maize yields have declined, and as maize area has increased, presumably supplanting some wheat area, maize yield has increased, all else equal

The trends in soybean yield as explained by weather, soil, time, and crop area effects are remarkably similar to maize's, with one exception: 'trend yield growth' trajectories for soybean production across S_2, S_3, S_4, and S_5 counties are much more similar than they are for maize production across these same 4 county groups (see Appendix Text H).

Establishing a temporal baseline for the soil reclamation and climate change analysis

To estimate the effects that *changes* in climate and cropland soil capability could have on Midwestern maize and soybean yield I first estimate county-level yields for the base period 2000-2008 for each soil capability class. To do this I use observed explanatory variable levels from 2000-2008 and estimated model (2) results. The distribution of y_{jc} values – predicted 2000-2008 average annual yield of crop *j* in county *c* – for each $\{S_q; j\}$ combination are graphed in figure 2 (predicted yield distributions over the 9 year period are remarkably close to observed distributions; see Appendix Text I). As expected, the predicted average annual 2000-2008 county-level maize (first column of histograms) and soybean (second column of histograms) yield distributions shift to the right in soil class; distribution means become larger and county-level yields below any given yield level, for example, 100 bushels of maize per acre, become less probable as q increases.[iii]

Using soil resources more efficiently to increase recent maize and soybean production

Before estimating the future impact of investments in soil reclamation under climate change I explore how different Midwestern maize and soybean yields would have been from 2000-2008 under what I will call "marginal" soil reclamation. By marginal reclamation I mean reclaiming the soil enough in an area such that it mimics the soil capability of the representative acre from the next highest soil capability class. So, for example, marginal soil reclamation on an acre that belongs to set S_1 would mean that its soil capability is improved just enough to mimic the capability of the representative S_2 acre.[iv]

To estimate the counterfactual 2000-2008 S_q yield distribution with marginal soil reclamation, all else equal, I use the weather from S_q counties from 2000-2008 with S_{q+1}'s estimated yield functions where A_{jct}, A_{-jct}, and A_{wct} values are set equal to the average values observed from 2000-2008 *in* S_{q+1} *counties*.[v] I am not literally assuming that S_q counties would adopt the same exact relative land-use mix as S_{q+1} counties when reclaiming soil; instead recall that the harvested area variables help identify how the soil profile within a soil class is used at any given time. In other words, by using the $(q+1)^{\text{th}}$ class' annual average A_{jct}, A_{-jct}, and A_{wct} values and its estimated model coefficients to estimate the effect of reclamation in S_q counties I am essentially moving the soil typically cropped in S_{q+1} counties during 2000-2008, and how that soil interacted with weather and technological innovation trends, to S_q counties. For example, consider the counterfactual effect of marginal soil reclamation on maize yield from 2000-2008 in county *c* that belongs to soil capability class S_q. County *c*'s predicted maize yield in year *t* assuming that it acquires the soil capability used on a typical class *q*+1 field from 2000-2008 is given by,

$$y'_{mct} = \hat{\sigma}_{mq+1} + \hat{\gamma}_{1mq+1}t + \hat{\gamma}_{2mq+1}t + \hat{\gamma}_{3mq+1}GDD_{mct} + \hat{\gamma}_{4mq+1}GDD^2_{mct} + \hat{\gamma}_{5mq+1}PRECIP_{mct} + \hat{\gamma}_{6mq+1}PRECIP^2_{mct} + \hat{\gamma}_{7mq+1}\bar{A}_{mq+1} + \hat{\gamma}_{8mq+1}\bar{A}_{sq+1} + \hat{\gamma}_{9mq+1}\bar{A}_{wq+1} \qquad (2)$$

where $\hat{\gamma}_{kmq+1}$ indicates that the estimated coefficient from the S_{q+1} maize model, $\bar{A}_{jq+1}$ is the average percentage of county area used to harvest *j* across S_{q+1} counties over the years 2000-2008, and the maize growing season weather for year *t* is given by county *c*'s growing season weather for that year. Let $y'_{mc} = (\sum_{t=2000}^{2008} y'_{mct})/9$ give the average annual 2000-2008 county-level yield of maize in *c* such that its cropped soil has been reclaimed enough to become a typical acre in S_{q+1}. I calculate y'_{sc} in the same manner. The distribution of y'_{mc} and y'_{sc} values across set S_q for q = 1,…,4 are graphed in figure 3 (S_5 yields cannot be marginally improved).

As expected, marginal soil reclamation causes the distribution of average annual 2000-2008 county-level yields to shift to the right for all $\{S_1,\ldots,S_4; j\}$ combinations compared to the 2000-2008 distributions without marginal reclamation. For illustrative purposes assume that only the representative (mean) acre of maize and soybeans from each class $S_1,\ldots,S_4$ is marginally reclaimed. The representative acre of maize from class S_1 would have experienced the largest relative increase in annual average yield due to marginal reclamation, increasing by 17% (120.1 to 140.4 bushels per acre; see Appendix Text L). In other cases, the annual average yield improvement on the representative acre would have been small. For example, the representative soybean acre in S_3 would have increased its annual average yield only by 2% (42.9 to 43.7 bushels per acre) with marginal reclamation (see Appendix Text L).

However, marginal reclamation's biggest impact from 2000-2008 would have been found in the lower tail of each S_q's average annual county-level yield distribution. For example, to keep annual net revenues (production value less operating costs but before any reclamation costs) on a maize acre from falling below $150 during 2000-2008, Midwestern farmers had to produce approximately 140 bushels on the acre (USDA-ERS 2013). Marginal reclamation would have reduced the probability of the representative acre's average annual yield from falling below 140 bushels by 42%, 26%, 14%, and 16% for S_1, S_2, S_3, and S_4 counties, respectively. Similar reductions in the probabilities of low-yield outcomes would have held for soybeans as well (see Appendix Text L). Therefore, counterfactual marginal reclamation, all else equal, would have had a much more significant impact on the reduction in the risk of low yield outcome than on average annual yields.[vi]

Predicted Midwest maize and soybean yields at mid-century

Between the periods 1950-1958 and 2000-2008, average maize and soybean *GDD* across the six states examined in this paper barely changed. However, there was some variation within areas defined by soil capability class. The greatest absolute change was a 4.5% increase in S_1's average maize *GDD*. Interestingly, the greatest negative change in average *GDD* was also in the S_1 region as well: a -2.7% decline in average soybean *GDD*. Because Midwestern soybeans tend to be planted later and harvested earlier than maize (Sacks et al. 2010), these opposing trends indicate that temperatures during the height of the summer over S_1 counties had decreased a bit between 1950-1958 and 2000-2008 while temperature increases in the spring and fall more than made up for the slight midsummer decline. Changes in *PRECIP* have been more dramatic over this period for both crops as average maize *PRECIP* between 1950-1958 and 2000-2008 increased by 10% or more across most soil capability class areas. That wetter springs and falls have become more the norm over the six state area is evinced by the fact that maize *PRECIP* average changes were higher than soybean *PRECIP* average changes in all 5 soil capability categories (Baker et al. 2012; Appendix Text M).

Most climate models predict much more rapid climate change over these six states in the next 50 years than in the previous half-century (Backlund et al. 2012). Summer temperatures are expected to increase 2.2 to 3 degrees Celsius from the late 20^{th} century to the mid 21^{st} century over most of the study region (Girvetz et al. 2009, Appendix Text N). Given appropriate reactions in planting dates by strategic farmers this is expected to increase *GDD* for maize and soybeans in the Midwest by 200 to 400 or approximately 10 to 20% above 2000-2008 levels (Shively et al. 2008, Zavalloni et al. 2008). Predicted changes in the study area's growing season precipitation over the next 50 years are directionally mixed; it appears some areas will become a bit drier while other areas will become slightly wetter compared to previous levels. However there is a growing consensus that the upper Midwest will become even wetter in the spring (continuing a trend I have already detected from 1950-1958 to 2000-2008) and slightly drier in the summer months (Baker et al. 2012, Hatfield et al. 2013).

Agricultural technology and know-how will also increase over time. If we extrapolate estimates of model (1) out to 2050-2058, maize and soybean trend yield growth continue to increase at an increasing rate for all soil capability classes except S_1. In S_1 areas the trend growth from 2000-2008 to 2050-2058 is increasing at a decreasing rate for both crops (Appendix Text H). Whether the extrapolated productivity trajectories in Midwestern maize and soybeans production can be achieved given recent public divestments in agricultural R&D and expected climate change is uncertain. Several researchers claim that much of the increase in maize and soybean productivities seen from 1950 to early part of the 21st century in the Midwest were driven by high levels of US government R&D funding from 1950 to 1970 (e.g., Alston et al. 2009, 2010). Since 1970 government funding has dropped significantly (although some has been made up by more private company R&D) and it has been speculated that this will eventually reverberate in lower that historical yield gains (Long and Ort. 2010). Further, climate change may affect productivity growth: for example, David Lobell claims that each 1 degree Celsius increase in average temperatures results in a 5 to 6 year setback in trend yield growth (Hertel 2011). Given a predicted 2.2 to 3 degrees Celsius increase in summer temperatures (see above) this means climate change could cause a 11 to 18-year delay in reaching the ‘no climate change’ 2050-2058 trend yield growth.

I use the following parameterized model to estimate the county-level yield of crop j in c for the years 2050-2058,

$$y_{jct+50} = \hat{\sigma}_{jcq} + \hat{\gamma}_{1jq}(t + x_{jc}) + \hat{\gamma}_{2jq}(t + x_{jc})^2 + \hat{\gamma}_{3jq}(\alpha_{jc} GDD_{jct}) \tag{3}$$

$$+\hat{\gamma}_{4jq}(\alpha_{jc} GDD_{jct})^2 + \hat{\gamma}_{5jq}(\theta_{jc} PRECIP_{jct}) + \hat{\gamma}_{6jq}(\theta_{jc} PRECIP_{jct})^2$$

$$+\hat{\gamma}_{7jq} A_{jct} + \hat{\gamma}_{8jq} A_{-jct} + \hat{\gamma}_{9jq} A_{wct} \qquad \text{for } t = 2000,\ldots,2008$$

where α_{jc}, and θ_{jc} and x_{jc} allow for the possibility of climate change and changes in the rate of yield productivity, respectively. The variable x_{jc} is set equal to 50 if I assume *j*'s trend yield growth in county *c* will continue into the future at the rate that it did for *j* in *c*'s soil capability class from 1950 to 2008 (the 'historical rate') and I set x_{jc} less than 50 if I assume technological progress in *c* will continue into the future at a rate lower than *j*'s historical rate in *c*'s soil capability class. The parameters α_{jc} and θ_{jc} indicate the expected value of county *c*'s annual GDD_{jct} and $PRECIP_{jct}$, respectively, for the years 2050 to 2058 relative to their 2000 to 2008 values. For example, if I set α_{jc} equal to 1.2 then GDD_{jct} for 2050 would by 20% greater than the GDD_{jct} in 2000, 20% greater in 2051 compared to 2001, etc. Finally, in the year 2050 the variable A_{jct} is equal to the percentage of county *c* in *j* harvested area in the year 2000, in 2051 A_{jct} is equal to the percentage of county *c* in *j* harvested area in the year 2001, etc.[vii] Finally, $y_{jc}^* = \left(\sum_{t=2000}^{2008} y_{jct+50}\right)/9$ is the average annual 2050-2058 county-level yield of *j* in county *c* given the 2000-2008 observations for A_{mct}, A_{sct}, and A_{wct} and assumptions regarding climate change and yield trend growth as specified by α_{jc}, θ_{jc}, and x_{jc}.

Given the discussion above regarding expected trends in *GDD*, *PRECIP*, and yield trend growth I define three representative 2050-2058 scenarios. Let the 'no change' future be given by $x_{jc} = 50$, $\alpha_{jc} = 1$, and $\theta_{jc} = 1$ for all *c* in all soil capability classes and both *j*. In other words, the 'no change' future assumes the unmodified extrapolation of all historical trajectories of productivity gains and no change in the climate between 2000-2008 and 2050-2058 over the six states. I also define two alternative scenarios where climate patterns and yield trend trajectories change. The 'worst' scenario, the scenario that would drag 2050-2058 yields down the most but is still squarely within the realm of possibility, is equal to $\alpha_{jc} = 1.2$, $\theta_{jc} = 0.9$, and $x_{jc} = 32$ across all c and j. The most benign or 'best' alternative, the scenario of change that would drag 2050-2058 yields down the least but is still squarely within the realm of possibility, is equal to $\alpha_{jc} = 1.1$, $\theta_{jc} = 1$, and $x_{jc} = 39$ across all c and j.

In figure 4 I present the distribution and means of average annual 2050-2058 county-level maize and soybeans yields under the two alternative scenarios of change for all soil capability classes. I also plot the mean of the distribution of average annual 2050-2058 county-level maize and soybeans yields under the 'no change' scenario for all soil capability classes. Therefore, depending on soil capability class and modeled future, I project an 8% to 28% decline in mean county-level maize yields and a 7% to 23% decline in mean county level soybean yields compared to 'no change' means by midcentury. The counties with the most marginal soils are affected the least by expected climate change simply because yield trend growth in these areas is already weak.

A closer look at expected 2050-2058 county-level yield distributions reveals several interesting trends. First, by 2050-2058 the distribution of annual average county-level maize yields across the S_4 and S_5 class have converged under both futures of change; this result is primarily driven by the higher rate of yield trend growth in S_4 counties compared to the extrapolated trend in S_5 counties. Therefore, soil capability is no longer a limiting factor in S_4 counties by 2050-2058 when it comes to maize production. Second, the divergence between the distribution of county-level maize yields in S_1 counties and the distributions across all other soil capability classes increases dramatically compared to the 2000-2008 gap. This is caused primarily by the accelerating yield trend growth in sets S_2 through S_5 versus the decelerating trend in the S_1 set of counties. Expected divergence between soybean yields on S_1 soils and yields in all other S_q soils is not as dramatic as it is with maize. While trend yield growth for soybeans is decelerating in S_1 counties as well, the acceleration of trend yield growth in the higher S_q is not as intense for soybeans as it is for maize.

Finally, the difference in maize and soybean productivity across the two alternative futures of change is large. To get an understanding of the gap consider the following. When I use the mean of annual 2050-2058 county-level yields for each soil capability class, assume 2000-2008 average net returns to a bushel of maize and soybeans from the six state area holds in 2050-2058 ($0.75 and $3.89 in 2000 $, respectively; USDA-ERS 2013), and the 2000-2008 areal distribution of maize and soybeans across the six states exists in 2050-2058 then the 'worst' scenario will generate $926 million and $946 million (2000$) less in average annual maize and soybean net returns, respectively, in the six state area than the more benign future. This loss is equivalent to 22% and 15% of average annual net return to maize and soybean production, respectively, in the six states from 2000-2008.

Finally, the impact of marginal soil reclamation on maize and soybean production from 2050-2058 on S_1 and S_2 soils is predicted to be significant (figure 5). (Marginal soil reclamation for 2050-2058 is modeled the same way it is for the counterfactual 2000-2008 marginal soil reclamation analysis.) Expected yield on the representative acre of maize and soybeans on S_1 soils is expected to increase by 39.4% to 41.8% and 13.9% to 14.0%, respectively (assuming the worst and best climate-yield trend scenarios, respectively) with marginal soil reclamation, all else equal. Notice how this completely reverses the predicted yield losses due to climate change for maize under both climate scenarios and for soybeans under the “Best” scenario (figure 5). On the representative S_2 acre marginal reclamation is expected to increase average annual maize and soybean yields by 2.7 to 4.4% and by 2.4% to 2.3%, respectively. In table 1 I summarize what these changes at the means might mean for economic returns.

However, the reduction in the risk of low yields may be more important to risk adverse farmers than any increase in average yields. For example, the risk of average annual maize yield on the representative acre from the S_1, S_2, and S_3 categories falling below 200 bushels from 2050-2058 under the ‘worst’ future scenario is 51%, 17%, and 7% less likely with marginal reclamation, respectively. Further, the risk of average annual maize yield on the representative acre from the S_1, S_2, and S_3 categories falling below 220 bushels from 2050-2058 under the ‘best’ future scenario is 61%, 28%, and 11% less likely with marginal reclamation, respectively (Appendix Text O). See table 2 for a similar analysis with soybeans.

Robustness Checks

I undertake several statistical tests to verify the robustness of the results discussed above. First, I test for any spatial autocorrelation in the model. Variation in weather across time is usually considered a random process, but patterns in weather across space can be highly correlated (Auffhammer et al. 2013). If a yield model accounts for all weather characteristics that affect crop growth then this spatial autocorrelation is a non-issue when it comes to model estimation. However, if my yield model omits one or more spatially correlated weather characteristics that affect crop growth, such as wind, humidity, or the number of days with extreme heat, then the standard errors of model (1)’s estimated coefficients will be biased (i.e., the standard errors of the estimated model coefficients will be larger once we correct for spatial autocorrelation). In other words, my earlier claims of strong statistical significance across most estimated coefficients of model (1) could be erroneous.

To correct for spatial autocorrelation in standard error estimates of model (1) I use a grouped bootstrap technique where years are resampled and replaced (Auffhammer et al. 2013; see Appendix Text P for the grouped bootstrap results). Summarizing the main findings of the analysis here, I find that using bootstrapping to correct for spatial autocorrelation has a negligible effect on the statistical significance of model (1)'s estimated coefficients. Across all $\{S_q; j\}$ combinations only a few variables that were statistically significant in the original estimate of (1) become statistically insignificant with grouped bootstrapping . To conclude, the spatial autocorrelation that does exist in my model has a negligible effect on the statistical strength of estimated results.

I am also concerned about the consistency of county membership in soil capability classes over time. The land capability class map I use to create each county's time-invariant L_c score and the sets of S_q has been constructed over the last 30 years (USDA-NRCS 2013). Therefore, it is possible that a county had a different L_c score and therefore belonged to a different soil capability class in the past than it does now. For example, extensive drainage tiling in a county at any point between 1950 and 2008 could have changed its capability class. If relatively large changes in L_c scores were frequent from 1950 to 2008 then my analysis is likely to be erroneous as class membership in many years would be incorrectly defined. For example, if one county currently in class S_4 was in class S_3 in the 1950s and 1960s and all other S_4 counties have been accurately classified from 1950 to 2008 then predicted yields for class S_4 are likely biased downward due to inclusion of lower soil capability yield observations in the portion of the dataset coded as S_4 counties.

However, there are several reasons to believe that county movement across capability categories over time is not a pervasive phenomenon. First, according to Robert R. Dobos, Soil Scientist at the USDA's National Soil Survey Center, once land has "been assigned [a soil capability classification], it is unusual for the classification to be changed. This can be problematic when adjacent states do not agree on the [classification] of a soil. But, by and large, the class is pretty stable…" (*personal communication*). Further, Mr. Dobos does not think soil reclamation projects are widespread currently.[viii] Therefore, significant changes in L_c since the 1980s and 1990s would appear to be rare and changes in a counties S_q membership even rarer given that a change in L_c does not always result in a shift to a different soil capability class.

Next I consider the period between the 1950s and the 1970s, before the advent of the soil capability maps and Mr. Dobos' professional recollections. First, I identify counties that experienced a structural shift in yield patterns between the periods 1950-1979 and 1980-2008 relative to the overall performance of their soil capability class cohort that cannot be explained by relative changes in weather or intra-county use of croplands. In such cases, a change in soil capability is one of the few omitted variables that could explain the structural shift in the performance of a county relative to its cohort over time.[ix] Next I re-estimate model (1) for all $\{S_q; j\}$ combinations only using the counties that did *not* experience an unexplained structural shift in yield of j relative to its cohort. In other words, I re-estimate model (1) only using counties that offer no evidence of a change in soil capability class between the periods of 1950-1979 and 1980-2008. If model estimates with the subset of retained counties are the same as model estimates with the full set of counties for all $\{S_q, j\}$ combinations then I can conclude that inclusion of counties that *may* have changed soil capability class between 1950 and 2008 in my dataset does not ultimately invalidate the conclusions I have reached and described above.

Specifically, to run this test I estimate the following for each $\{c, j\}$ combination 3 times,

$$y_{jct} = \alpha_{0jc} + \alpha_{1jc}\bar{y}_{js_q(c)t} + \alpha_{2jc}GDD_{jct} + \alpha_{3jc}GDD_{jct}^2 + \alpha_{4jc}PRECIP_{jct} + \alpha_{5jc}PRECIP_{jct}^2 + \alpha_{6jc}A_{jct} \tag{4}$$

once for the period 1950 to 1979, another for the period 1980 to 2009, and finally for the period 1950 to 2009. The variable $\bar{y}_{js_q(c)t}$ is the average county-level yield of crop *j* in year *t* across all counties that belong to *c*'s soil capability class. Therefore, the estimate of α_{1jc} will indicate how county *c*'s yield over time fits into the yield distribution of its county cohort over time controlling for weather and *j*'s areal distribution in *c*. Assuming that $\bar{y}_{js_q(c)t}$ is relatively insensitive to a change in the soil capability of a few of its county members over time,[x] any structural change in the estimate of model (4) for *c* means that *c* has, over time, significantly changed its performance relative to its cohort. I interpret such structural change as indirect evidence of a possible soil capability change, for good or bad, in county *c* (soil capability can erode over time as well; Quine and Zhang 2002, Cruse and Herndl 2009, Becklund et al. 2012). Statistical evidence for structural change in county *c* for crop *j* between period 1950-1979 and 1980-2009 is found with a Chow Test. Any county *c* for a given crop *j* that cannot support the null hypothesis of no structural change at a p-level of 0.05 is dropped from crop *j*'s dataset.

After I re-estimate model (1) for all $\{S_q; j\}$ combinations only using the counties *not* dropped from *j*'s dataset I use 2000-2008 explanatory variable data from the remaining counties to estimate the distribution of 2000-2008 county-level yield averages for each crop *j* across each soil capability class. The striking similarity between the predicted distributions with all counties (figure 2) and those estimated with the retained counties after the Chow Test indicates that the results of this analysis are insensitive to the use of the full or reduced datasets (see Appendix Text Q for details) and that any instances of counties switching soil capability classes over time do not affect my main conclusions.

Discussion

In this paper I have estimated the functional relationships between maize and soybean yield and growing season weather, soil capability, and time in six Midwestern US states. I use data on the allocation of land use within a county to control for the intra-county allocation of soils over different crops. By using 58 years of data I capture a wide variety of weather years, including some that may be very similar to typical years under future climates.

First, I find that small investments in soil reclamation on the least capable cropped soils significantly reduce the likelihood of very low yield outcomes under alternative future climates. Second, assuming 2000-2008 average net returns to a bushel of maize and soybeans, marginal soil reclamation means an expected extra \$45.26 and \$26.98 (2000 \$) of net returns per acre per year on a representative S_1 field in maize and soybeans, respectively (not including the private amortized costs of marginal soil reclamation). Given that the net return on the average Midwestern maize and soybean acre was \$95 and \$178 over the 2000-2008 period (2000 \$), respectively, gains from marginal soil reclamation on the leas capable soils could be substantial. Overall I have shown that marginal soil reclamation on the least capable Midwestern soils can enhance social welfare under expected climate change *assuming reclamation costs are reasonable*.

Therefore, the next essential task for economists and agronomists is to identify exactly where and what types of reclamation projects (e.g., establishing major drainage facilities, building levees or flood-retarding structures, providing water for irrigation, removing stones, or large-scale grading of gullied land, etc.) would most cost-effectively generate capability improvements similar to my ‘marginal’ improvements. Such an analysis will require the creation of a map of marginal soil reclamation costs *and* a more detailed map of potential returns to this investment. Ideally, the potential returns map will include the ecosystem service benefits of soil reclamation as well, including less soil erosion and better local water quality (Bossio et al. 2010, Smith et al. 2012). Given that soil reclamation also provides a stream of public goods a discussion on soil reclamation governance also needs to occur. To what extent should regulatory agencies promulgate soil reclamation incentive polices? To what extent will reclamation be undertaken by private farmers on their own accord? How much technical information and assistance will the regulatory agencies need to provide to promote private reclamation?

In his latest book, historian George Parker (2013) tells the fascinating story of climate change and agricultural practices in 17th century Europe and Asia. During that century, a vicious cycle of extreme weather (the “Little Ice Age”), wars, and disease reduced crop yields across the globe and ultimately led to the loss of a third of the world’s population. Yield depression caused by changes in weather, the decrease in supply of farm labor, and ultimately the decline in the global demand for food led to global abandonment of marginal cropland; only the most productive soils could generate positive economics returns for their owners and sharecroppers by the tail end of the 17th century. In that century abandonment of marginal land was the optimal response to climate and societal conditions. In this century abandonment of marginal cropland could lead to a global crisis. Unlike the 17th century, global population is expected to greatly expand this century, by 32% from 2013 to 2050 alone.[xi] Given this growing global population and the expected yield depression in many parts of the world due to expected climate change, more intensive use of marginal croplands, those still used currently and those recently abandoned, will be necessary to avoid the farming of the globe's remaining natural ecosystems and a massive increase in global agriculture's impact on the environment. I have shown that we can make the more marginal croplands much more productive with marginal investments in soil reclamation. Now a program that strategically identifies the most promising reclamation projects needs to be established.

My analysis could be improved in several ways. First, my analysis is based on crop and famer reaction to weather in the past. As the climate evolves Midwestern farmers and crop scientists will adapt in various ways. These adaptations may lead to modified maize and soybean varieties that do not react to weather the same way they did from 1950 to 2008. Or technological breakthroughs could lead to completely different trends in yield growth in the future. A richer analysis of potential farmer and the agricultural sector's reaction to climate change and greater demand from a burgeoning global population could improve my research.

One could also question the preciseness and usefulness of my broad soil capability measure. The coarse index of soil capability used here may not be subtle enough to accurately capture the impact and meaning of marginal soil reclamation and prove useful in identifying the places where marginal reclamation of soil would be most productive. Further, my study says nothing on the impact of improvements in soil quality that do not involve reclamation. For example, Cong et al. (2013) and de Vries et al. (2013) have shown how investments in a field's soil organic carbon stock can be an optimal strategy for a risk adverse farmer under a more volatile climate. Field studies that explore adaptation possibilities to climate change are also well-positioned to incorporate other potentially important drivers of agricultural productivity such as pest abundance and mix. The omission of pest abundance and mix in a yield model that is used to analyze future yields could be problematic as discontinuous changes in pest regimes are expected under climate change (e.g., Diffenbaugh et al. 2008).

One could also question the appropriateness of my weather data for modeling past and future yields. For example, Schlenker and Roberts (2009) use hourly temperature data from 1950 to 2005 to pinpoint the effect of temperature on US maize and soybeans yield (recall I use monthly averages). However, my results are very similar to theirs despite the coarser climate data (see Appendix Text R). Therefore, it does not appear my study was adversely affected by the coarser weather data.

Finally, as I mentioned above, this research would be conducted differently if I had cropland maps at the field level back to 1950. Such maps would allow me to determine exactly what soils each crop is grown on and I would not have to rely on the assumption that a county's overall soil profile matches the soil profile used for maize and soybeans in that county. Unfortunately, digital maps of cropland at the pixel level for the entire study region have only been published since 2007 (http://nassgeodata.gmu.edu/CropScape/).

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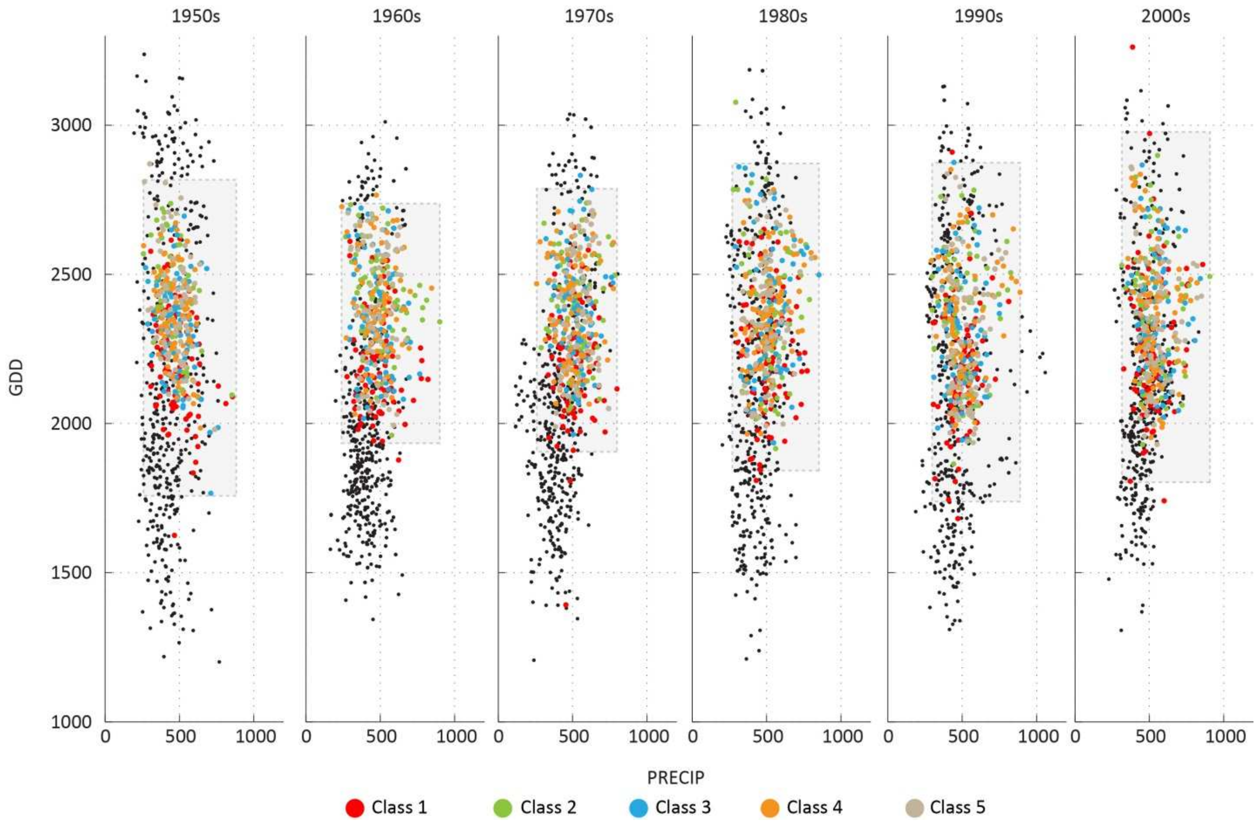


Figure 1: GDD_{mct} and $PRECIP_{mct}$ of the 10 best and worst measures of Y_{mct} for each year t across all soil capability classes. Results are separated by decade. In each decadal subplot the colored (black) dots indicate the ten best (worst) county-level yields observed in a soil class in a given year. Because I use 5 soil classes there are 500 colored dots (100 dots of each color) and 500 black dots in each subplot (I do not differentiate the worst yields by soil class). The grey box in each plot indicates the bounds of the colored dots less the high and low GDD_{mct} outlier for that decade. Counties with any unclassified soil area were not eligible for ranking. See Appendix Text C for a similar soybean figure.

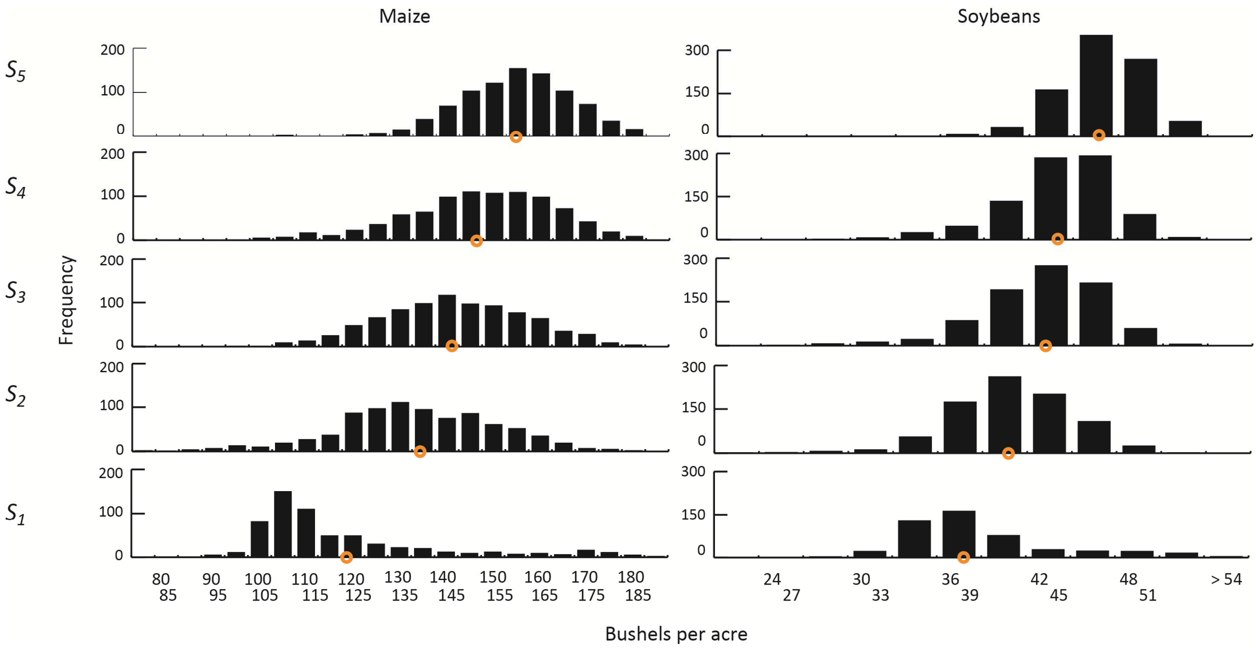


Figure 2: **Histograms of predicted 2000-2008 average annual county-level maize and soybean yields by soil class S_q.** The orange circles indicate the mean value of each distribution. Counties with any unclassified soil area are not included.

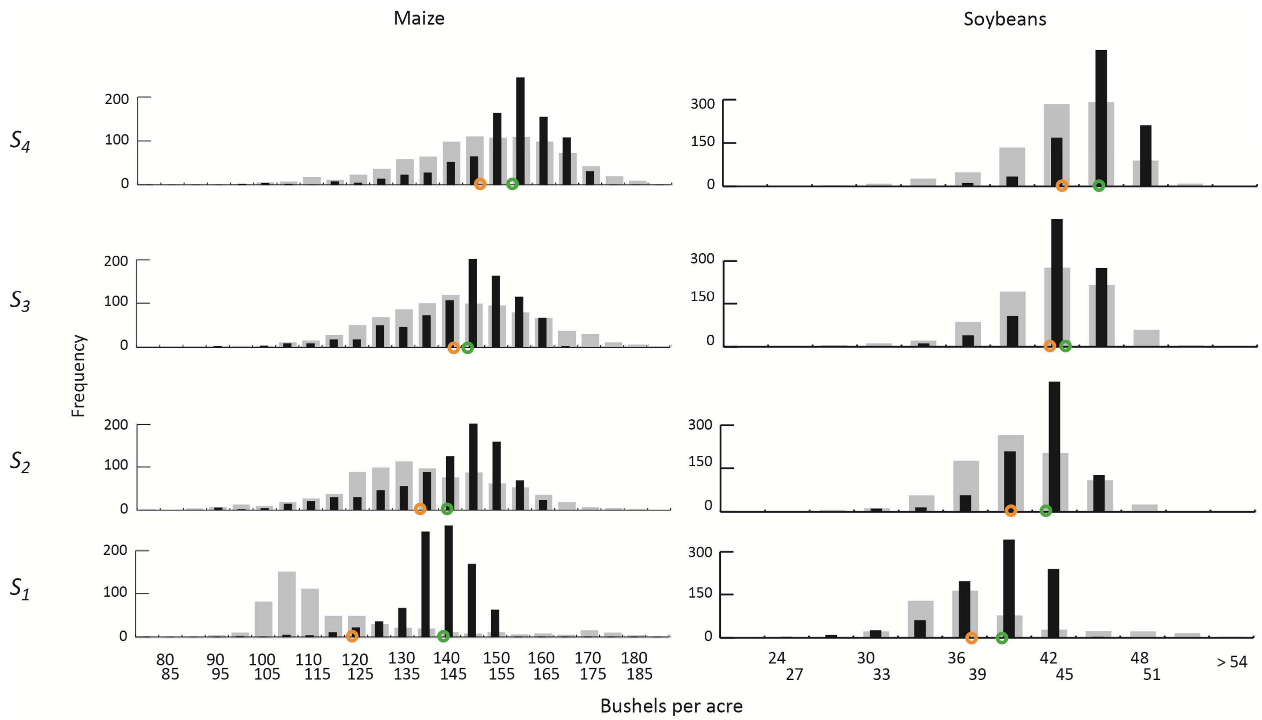


Figure 3: Histograms of predicted 2000-2008 average annual county-level maize and soybean yields without and with marginal soil reclamation. The gray bars and orange circles represent the distribution and mean, respectively, of county-level average yields without marginal soil reclamation (the same distributions as figure 2). The black bars and green circles represent the distribution and mean, respectively, of county-level average yields *with* marginal soil reclamation. Counties with any unclassified soil area are not included.

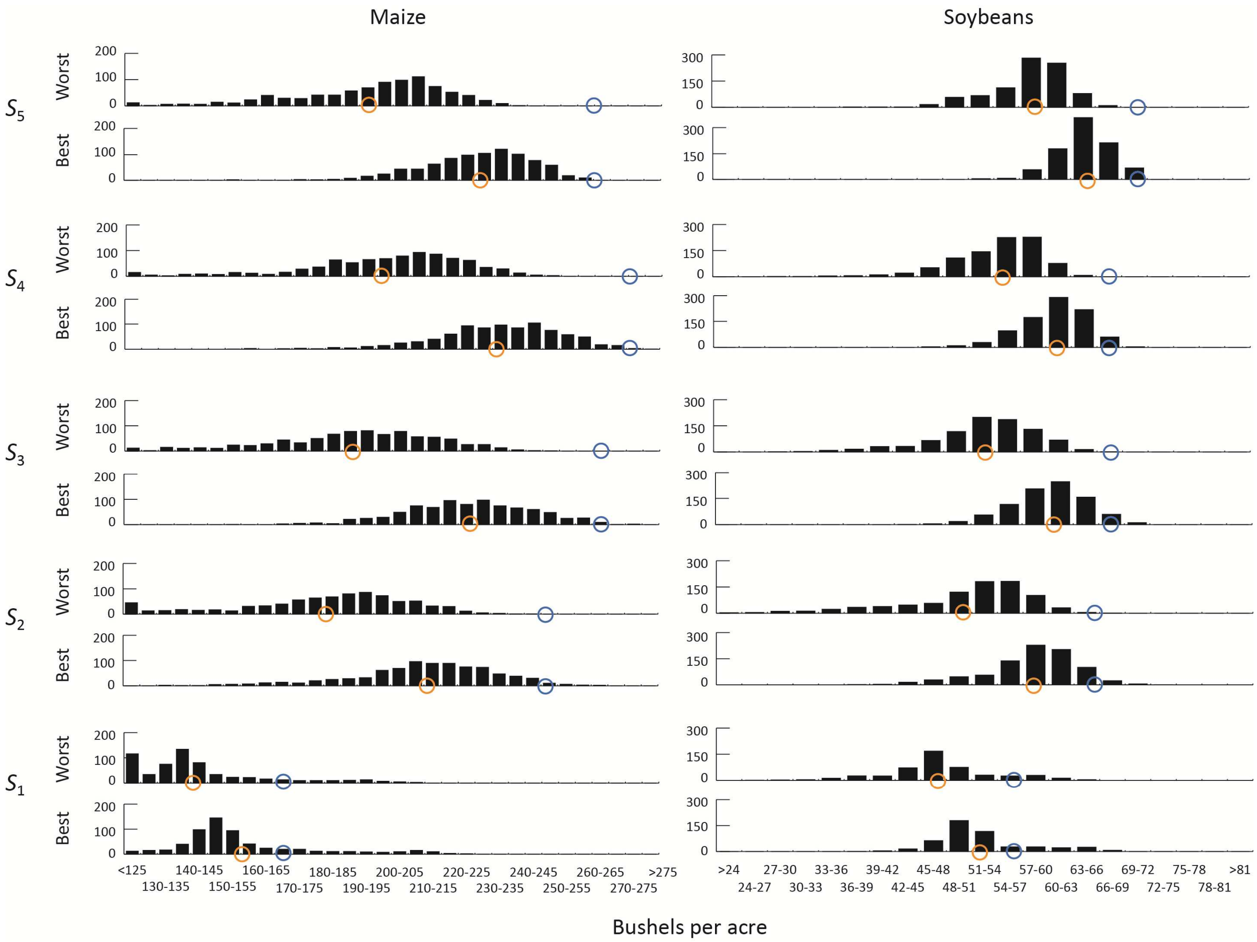


Figure 4: Histograms of predicted 2050-2058 average annual county-level maize and soybean yields by soil capability class under two alternative climate scenarios. The "Best" climate scenario assumes a 10% increase in GDD_{mct} and GDD_{sct} across the entire study area, no change in $PRECIP_{mct}$ and $PRECIP_{sct}$ and an 11 year slowdown in yield trend growth. The "Worst" climate scenario assumes a 20% increase in GDD_{mct} and GDD_{sct} across the entire study area, a 10% decrease in $PRECIP_{mct}$ and $PRECIP_{sct}$ across the entire study area, and 18 year slowdown in yield trend growth. The orange circles indicate the mean value of each distribution while the blue circles indicate the mean value of the baseline distribution (no climate change and no slowdown in yield trend growth). Counties with any unclassified soil area are not included.

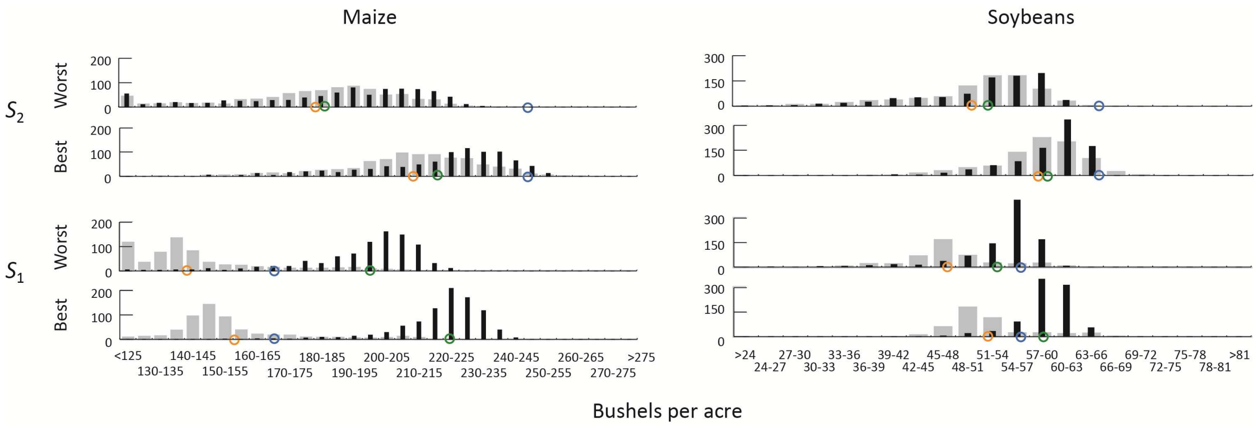


Figure 5: Histograms of predicted 2050-2058 average annual county-level maize and soybean yields without and with marginal soil reclamation under two alternative climate scenarios on soil capability classes 1 and 2. The gray bars and orange circles represent the distribution and mean, respectively, of county-level average yields without marginal soil reclamation (the same distributions as figure 4). The black bars and green circles represent the distribution and mean, respectively, of county-level average yields *with* marginal soil reclamation. Counties with any unclassified soil area are not included. The blue circles indicate the mean value of the baseline distribution (no climate change and no slowdown in yield trend growth). See the figure 4 legend for details on the future scenarios.

Table 1. Expected monetary gains in net returns to maize and soybean production with soil reclamation under alternative 2050-2058 climates

	"Best" Climate Scenario		"Worst" Climate Scenario	
S_q	**Maize**	**Soybeans**	**Maize**	**Soybeans**
1	$48.84	$28.31	$41.67	$25.64
2	$6.99	$5.18	$3.61	$4.74

Notes. Assumes average net returns to an acre of maize and soybeans over the six state area was $0.75 and $3.89 in 2000 $, respectively (equivalent to 2000-2008 average net return to a bushel of maize and soybeans over the six state area; USDA-ERS 2013). Does not include private amortized costs of marginal soil reclamation.

Table 2. Expected reductions in the probability of low yield outcomes with soil reclamation under alternative 2050-2058 climates

	Maize		**Soybeans**	
S_q	**Yield being below 220 bushels / acre under "Best" scenario**	**Yield being below 200 bushels / acre under "Worst" scenario**	**Yield being below 57 bushels / acre under "Best" scenario**	**Yield being below 54 bushels / acre under "Worst" scenario**
1	0.6142	0.5116	0.6661	0.5229
2	0.2778	0.1729	0.1124	0.0966
3	0.1142	0.0728	0.0390	0.0218

Appendix to "Reclaiming soils to sustain maize and soybean productivity in the Midwestern US given climate change"

Appendix Text A. Annual county-level growing degree day and growing season precipitation data for maize and soybeans

First, I collected monthly temperature averages and precipitation levels for the years 1950 through 2008 for each 0.5 degree grid cell in the six state area (CRU 2010). Then, using a gridded map that gives growing season dates for crop *j* (Sacks et al. 2010), I calculated *j*'s growing degree days (GDD_{jct}) and growing season precipitation ($PRECIP_{jct}$) in each cell for the years 1950 through 2008. Temperature readings only added to the *GDD* measure if they were 5 degrees Celsius or greater and they occurred during the crop's growing season. The code to convert monthly daytime temperature averages and monthly precipitation amounts to *GDD* and *PRECIP* comes from Jamie Gerber, Institute of the Environment, University of Minnesota. A county's time series of growing season weather was set equal to that of the grid cell closest to the county's centroid. Contact the author for a copy of the MATLAB code that converts monthly average temperature data into GDD_{jct} for maize and soybeans.

Appendix Text B. County-level soil capability measures, the creation of soil capability class categories, and county membership in classes

The native USDA-NRCS (2013) capability classification map places all soils in one of eight capability classes, known as Land Capability Classifications (LCCs). The risks of soil damage or limitations in use become progressively greater from class I to class VIII. Soils in the first four classes under good management are capable of producing adapted plants, such as forest trees or range plants, and the common cultivated field crops and pasture plants. Soils in classes V, VI, and VII are suited to the use of adapted native plants. Some soils in classes V and VI are also capable of producing specialized crops, such as certain fruits and ornamentals, and even field and vegetable crops under highly intensive management involving elaborate practices for soil and water conservation. Soils in class VIII do not return on-site benefits for inputs of management for crops, grasses, or trees without major reclamation.

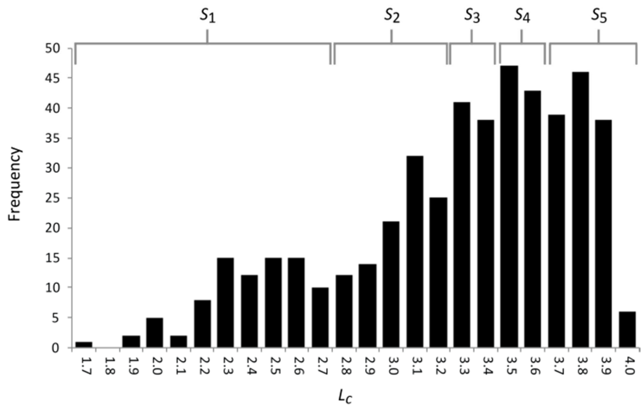
Let L_c be given by,

$$L_c = 4L_{c1} + 3L_{c2} + 2L_{c3} + L_{c4} + 0L_{cU} \quad \text{(I)}$$

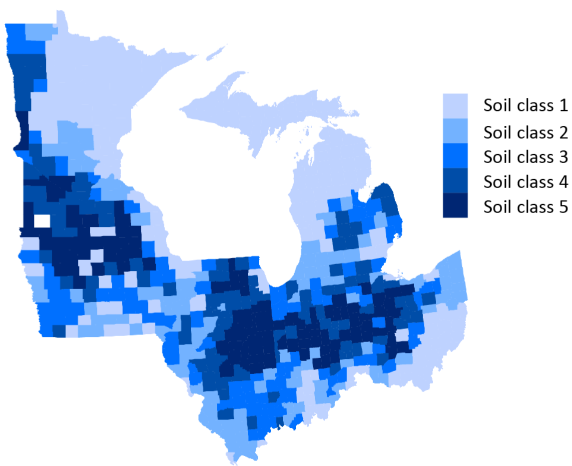
where L_{c1} is the fraction of county c's area in land capability classes (LCCs) 1 and 2, L_{c2} is the fraction of county c's area in LCCs 3 and 4, L_{c3} is the fraction of county c's area in LCCs 5 and 6, L_{c4} is the fraction of county c's area in LCCs 7 and 8, and L_{cU} is the fraction of county c's soil area that has not been classified. The lower the density of highly capable soils in county c, the lower its value of L_c. Appendix Text B Table 1 indicates how L_c values were binned into soil capability classes. Appendix Text B Figure 1 indicates the distribution of L_c scores and the binning of soil capability classes. Appendix Text B Figure 2 indicates the spatial distribution of soil capability classes.

Appendix Text B Table 1

S_q	Range in L_c
1	[0.000, 2.785]
2	(2.785, 3.218]
3	(3.218, 3.437]
4	(3.437, 3.680]
5	(3.681, 4.000]



Appendix Text B Figure 1



Appendix Text B Figure 2

Appendix Text C. Soybean version of Figure 1.

Appendix Text C Figure 1: *GDD_{sct}* and *$PRECIP_{sct}$* of the 10 best and worst measures of *Y_{sct}* for each year *t* across all soil capability classes. Results are separated by decade. In each subplot the dots other than those shaded black indicate the ten best county-level yields observed in a soil class in a given year. In each subplot the black dots indicate the ten worst county-level yields observed in each soil class in a given year. Because I use 5 soil classes there are 500 non-black dots (100 dots of each color) and 500 black dots in each subplot (I do not differentiate the worst yields by soil class). The grey box in each plot indicates the bounds of the colored dots less the high and low *GDD_{sct}* outlier for that decade. Counties with any unclassified soil area were not eligible for ranking and therefore are not represented in the figure above.

Appendix Text D. OLS estimates of the cropping success model (model 1)

Let the ratio of harvested to planted acres of crop *j* in county *c* in year *t* be given by R_{jct} where $R_{jct} = A_{jct} / P_{jct}$ and P_{jct} indicates the percentage of county *c*'s area planted in crop *j* in year *t*. For maize P_{jct} refers to all planted corn, whether it eventually fails, is used for grain, or used for silage (recall that A_{mct} just refers to maize for grain harvested area). A model that explains planted area harvest rates for crop *j* for *t* = 1950 to 2008 is given by,

$$CH_{jct} = \alpha_{0j} + \alpha_{1j}GDD_{jct} + \alpha_{2j}PRECIP_{jct} + \alpha_{3j}GDD_{jct}^2 + \alpha_{4j}PRECIP_{jct}^2 + \alpha_{5j}I_{c(S_q)} + \alpha_{6j}D_{jc(state)t} + \alpha_{7j}t \quad \text{(II)}$$

where $I_{c(S_q)}$ indicates which soil capability class that county *c* belongs to and $D_{jc(state)t}$ indicates state-level farm-gate per bushel price for each year and commodity where *c*(*state*) indexes what state county *c* belongs to and assigns state-level prices to counties accordingly. I expect the rate of cropping success to decrease as *GDD* and *PRECIP* fall to very low or high levels because extreme weather incidences are likely to drive *GDD* and *PRECIP* much lower or higher than normal. (Not always, however. Suppose the first part of the growing season is very cold and the second part is abnormally hot. The composite season GDD could indicate a typical year.) In other words, I hypothesize a statistical estimate of model (II) to generate a "inverted U" relationship between each weather variable and cropping success, all else equal (positive signs for α_1 and α_2 and negative signs for α_3 and α_4). Further, crops on more capable soils should be more resilient to extreme weather that could lead to crop failure. If this is the case, estimated α_5 should be positive given that increases in $I_{c(S_q)}$ indicates greater capability. In addition, crop failure rates could also be partly explained by economic data. If the farm-gate price is low enough it may not be cost-effective for a farmer to spend additional resources to maintain and harvest a crop that has become stressed. Therefore, I hypothesize estimated α_6 will be positive, all else equal. (I assume that when a decision on whether or not to invest in a distressed crop has to be made the farmer has a fairly good idea of what the farm-gate price for the crop will be at harvest time. In other words, while the farm-gate price will have not been revealed to the farmer at the time of decision I assume he can make a fairly accurate guess given market and weather conditions.) Finally, failure rates may become less acute over time as agricultural technology and farm management has improved; therefore, estimated α_{7j} is likely to be positive. Other than the estimated coefficient on $D_{mc(state)t}$ (the maize farm-gate price), ordinary least squares estimates of model (II) for maize and soybeans from 1950 to 2008 generate estimated coefficients, all statistically significant at the p = 0.01 level, that conform to expectations. See Appendix Text D Table 1.

Appendix Text D Table 1

	Maize			**Soybeans**		
	Est. Coefficients	**Std. Err.**	**P-value**	**Est. Coefficients**	**Std. Err.**	**P-value**
Intercept	-341.60***	10.71	0.00	37.25***	4.25	0.00
GDD_{jct}	0.19***	2.26E-03	0.00	0.03***	1.07E-03	0.00
$PRECIP_{jct}$	0.06***	3.37E-03	0.00	0.01***	1.20E-03	0.00

	Maize			Soybeans		
	Est. Coefficients	**Std. Err.**	**P-value**	**Est. Coefficients**	**Std. Err.**	**P-value**
GDD_{jct}^2	-3.59E-05***	4.96E-07	0.00	-5.98E-06***	2.56E-07	0.00
$PRECIP_{jct}^2$	-4.60E-05***	3.23E-06	0.00	-1.28E-05***	1.29E-06	0.00
Soil Class (S_c)	2.94***	0.05	0.00	0.33***	0.02	0.00
Farm gate price (D_{jct})	-0.50***	0.11	0.00	0.07***	0.02	0.00
Year (t)	0.08***	0.01	0.00	0.01***	2.10E-03	0.00
R^2	0.622			0.107		
F value	4808			282		
N	20,433			16,527		

Notes: Asterisk ('***') denote variables significant at a 1% level. Counties with any unclassified soils were not included in the regression.

Appendix Text E. Historic relationship between yield and soil capability class

Appendix Text E Table 1: Average annual per acre county-level yields from 1950-2008 in each soil capability class

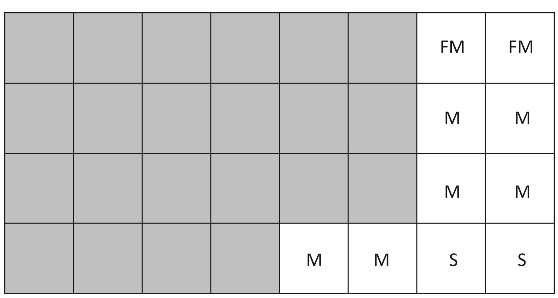
	Maize			**Soybeans**		
S_q	**Mean County-Level Yield**	**Std. Dev.**	**Coefficient of Variation**	**Mean County-Level Yield**	**Std. Dev.**	**Coefficient of Variation**
1	81.41	32.85	0.40	28.40	9.38	0.33
2	93.71	36.16	0.39	30.54	9.57	0.31
3	98.56	37.23	0.38	32.11	9.67	0.30
4	102.21	38.24	0.37	33.00	9.91	0.30
5	108.84	38.55	0.35	35.28	9.71	0.28

Notes: Counties with any unclassified soils were not included in the construction of these summary statistics.

Appendix Text F. Creation of omitted land use area variable

This residual land use category includes all other agricultural uses, including failed maize and soybeans acres, and non-agriculture uses such as urban areas, forests, etc. Land allocation statistics are straightforward to calculate at Midwest latitudes because double–cropping does not occur. For example, land used for winter wheat is harvested in the summer and planted with a restorative cover crop in the fall; spring wheat is harvested later in the year but eventually its land is also covered with alfalfa or something similar. In other words, there is one productive use for each acre of land each year

If maize or soybeans fields in a county in year *t* failed, the failure was soon enough to be planted over, and the second planting is harvested then the omitted land area statistic is given *approximately* by $100 - A_{jct} - A_{-jct} - A_{wct}$ because of some double-counting. For example, consider the following fictitious county where each grid is 100 acres, 'M' means the 100 acres grid was harvested for maize, 'S' means the 100 acres grid was harvested for soybeans, 'FM' means the 100 acres was planted with maize but it failed, and all other grids are urban areas (see Appendix Text F Figure 1). If *j* = maize then $A_{sct} = \left(\frac{200}{3200}\right) \times\ 100 = 6.25$, $A_{wct} = 0$, A_{mct} equals 18.75, 21.9, or 25 depending on any replanting success, and all other land uses is 75 (urban plus failed maize). If there is no replanting success then 100 – 18.75 – 6.25 – 0 = 75% of the county's area is in the residual land use category. If there is 100 acres that are successfully replanted then 100 – 21.9 – 6.25 = 100 – 28.15 = 71.85% of the county's area is in the residual land use category.



Appendix Text F Figure 1

Appendix Text G. Fixed effects estimate of model (1)

Appendix Text G Table 1: Fixed effects estimate of model (1) for *j* = maize, –*j* = soybeans

	Soil Capability Class S_q									
	1		2		3		4		5	
	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value
GDD_{jct}	0.14	0.00	0.13	0.00	0.18	0.00	0.23	0.00	0.29	0.00
$PRECIP_{jct}$	0.12	0.00	0.16	0.00	0.16	0.00	0.19	0.00	0.27	0.00
GDD_{jct}^2	$-3.3x10^{-5}$	0.00	$-3.3x10^{-5}$	0.00	$-4.3x10^{-5}$	0.00	$-5.6x10^{-5}$	0.00	$-6.9x10^{-5}$	0.00
$PRECIP_{jct}^2$	$-1.0x10^{-4}$	0.00	$-1.4x10^{-4}$	0.00	$-1.4x10^{-4}$	0.00	$-1.8x10^{-4}$	0.00	$-2.4x10^{-4}$	0.00
T	15.8	0.00	-24.2	0.00	-32.5	0.00	-31.3	0.00	-11.0	0.00
t^2	$-3.7x10^{-3}$	0.00	$6.5x10^{-3}$	0.00	$8.6x10^{-3}$	0.00	$8.3x10^{-3}$	0.00	$3.2x10^{-3}$	0.00
A_m	1.85	0.00	1.04	0.00	0.94	0.00	0.99	0.00	0.96	0.00
A_s	1.96	0.00	0.36	0.00	0.41	0.00	0.23	0.00	0.08	0.13
A_w	-1.62	0.00	-0.05	0.71	-0.08	0.35	-0.17	0.01	0.27	0.00
Con.	-17090	0.00	22305	0.00	30493	0.00	29207	0.00	8881	0.02
N	4927		5622		5708		5827		5782	
R^2										
within	0.77		0.80		0.81		0.83		0.84	
between	0.73		0.54		0.59		0.56		0.21	
overall	0.73		0.75		0.78		0.79		0.80	

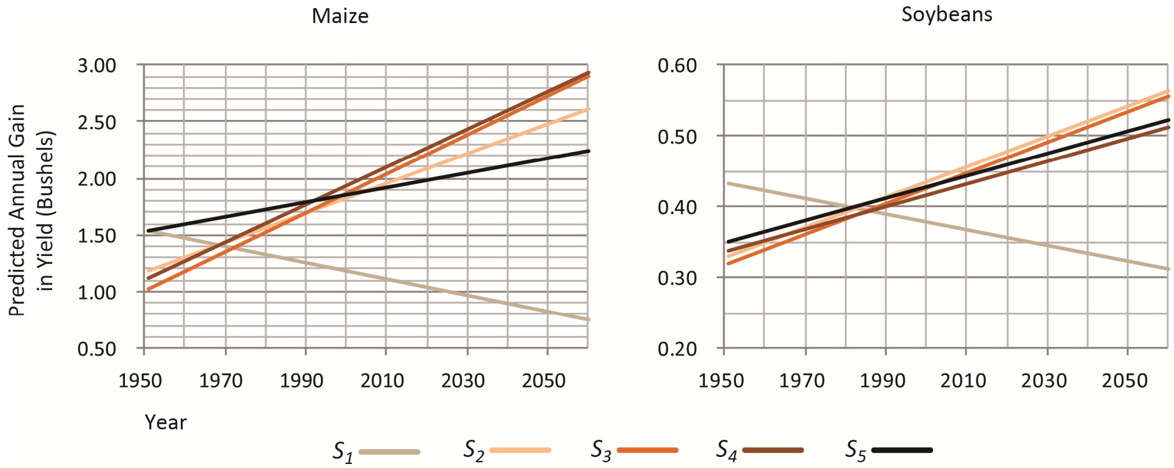
Note: STATA uses an estimated constant coefficient that averages the constant and fixed effect coefficients; see http://www.stata.com/support/faqs/stat/xtreg2.html.

Appendix Text G Table 2: Fixed effects estimate of model (1) for –*j* = maize, *j* = soybeans

	Soil capability class									
	1		2		3		4		5	
	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value	Est. Coeff.	p-value
GDD_{jct}	0.06	0.00	0.08	0.00	0.09	0.00	0.09	0.00	0.09	0.00
$PRECIP_{jct}$	0.05	0.00	0.05	0.00	0.05	0.00	0.07	0.00	0.09	0.00
GDD_{jct}^2	$-1.5x10^{-5}$	0.00	$-1.8x10^{-5}$	0.00	$-2.0x10^{-5}$	0.00	$-2.1x10^{-5}$	0.00	$-2.1x10^{-5}$	0.00
$PRECIP_{jct}^2$	$-4.2x10^{-5}$	0.00	$-4.9x10^{-5}$	0.00	$-5.0x10^{-5}$	0.00	$-6.6x10^{-5}$	0.00	$-8.6x10^{-5}$	0.00
t	2.63	0.04	-3.86	0.00	-3.91	0.00	-2.79	0.00	-2.76	0.01
t^2	$-5.6x10^{-4}$	0.09	$1.1x10^{-3}$	0.00	$1.1x10^{-3}$	0.00	$8.0x10^{-4}$	0.00	$8.0x10^{-4}$	0.00
A_m	0.54	0.00	0.25	0.00	0.25	0.00	0.21	0.00	0.23	0.00
A_s	0.16	0.00	$2.1x10^{-3}$	0.92	0.02	0.12	0.04	0.01	0.02	0.11
A_w	-0.54	0.00	-0.12	0.00	0.02	0.41	0.02	0.40	0.09	0.00
Con.	-3053	0.02	3356	0.00	3409	0.00	2294	0.01	2247	0.03
N	3368		5581		5706		5810		5782	
R^2										
within	0.71		0.75		0.77		0.78		0.78	
between	0.66		0.67		0.82		0.77		0.67	
overall	0.68		0.73		0.78		0.77		0.77	

Note: STATA uses an estimated constant coefficient that averages the constant and fixed effect coefficients; see http://www.stata.com/support/faqs/stat/xtreg2.html.

Appendix Text H. Trend yield growth



Appendix Text H Figure 1: Predicted trend yield growth for both crops in each soil class category. A plot point for S_q on graph *j* is estimated by calculating $\hat{\gamma}_{1jq}t + \hat{\gamma}_{2jq}t^2 - \hat{\gamma}_{1jq}(t - 1) - \hat{\gamma}_{2jq}(t - 1)^2$ and then plotting this *y*-axis value at the x-value of t.

Appendix Text I. Predicted and observed average annual county level yields for 2000-2008 across all 5 soil capability classes

Let $y_{jc} = \left(\sum_{t=2000}^{2008} y_{jct}\right)/9$ be the predicted average annual county-level 2000-2008 per acre yield of crop *j* in county *c* where,

$$y_{jct} = \hat{\sigma}_{jcq} + \hat{\gamma}_{1jq}t + \hat{\gamma}_{2jq}t + \hat{\gamma}_{3jq}GDD_{jct} + \hat{\gamma}_{4jq}GDD_{jct}^2 + \hat{\gamma}_{5jq}PRECIP_{jct} + \hat{\gamma}_{6jq}PRECIP_{jct}^2 + \hat{\gamma}_{7jq}A_{jct} + \hat{\gamma}_{8jq}A_{-jct} + \hat{\gamma}_{9jq}A_{wct} \quad \text{(III)}$$

$\hat{\sigma}_{jcq}$ indicates the average constant coefficient for S_q, and the $\hat{\gamma}_{kjq}$ indicates the estimated coefficient for crop *j* in soil class *q* in county *c* that is a member of set S_q. (STATA uses an estimated constant coefficient, in this case $\hat{\sigma}_{jcq}$, that averages the constant and fixed effect coefficients; see http://www.stata.com/support/faqs/stat/xtreg2.html.)

See figure 2 for the distribution of y_{jc} (predicted average annual yield of crop *j* in county *c* from 2000-2008) values for all $\{S_q; j\}$ combinations. The means of these distributions, represented by y_{mq} and y_{sq} for each S_q, are given in Appendix Text I Table 1.

Finally, let $\sum_{t=2000}^{2008} Y_{jct}/9$ indicate the observed average annual per acre yield of crop *j* in county *c* from 2000-2008 and Y_{jq} the mean of the distribution across all *c* in the same soil class category,

$$Y_{jq} = \frac{\sum_{t=1}^{9} \sum_{c \in S_q} Y_{jct}}{9 \times n(q)} \quad \text{(IV)}$$

Appendix Text Table 1: Predicted and observed average annual yields from 2000-2008

S_q	1		2		3		4		5	
	Predicted Average Yields									
	Est.	**SD**	**Est.**	**SD**	**Est.**	**SD**	**Est.**	**SD**	**Est.**	**SD**
y_{mq}	120.1	20.14	136.0	17.07	144.1	15.27	149.5	15.72	157.1	11.69
y_{sq}	38.8	5.11	40.9	4.09	42.9	4.05	44.02	3.64	46.9	2.83
	Observed Average Yields									
Y_{mq}	121.1	28.91	138.7	25.98	146.5	24.03	151.0	24.70	158.6	21.36
Y_{sq}	38.2	9.01	40.5	7.69	42.4	7.86	43.2	7.77	46.3	6.97

Appendix Text K. The potential to strategically use the best soils for cropping in soil class 1 counties

As of 2001, there were more than 5.6 million private acres in LCCs I and II in the counties that form soil capability class 1 that were not in cropland but could be (Appendix Table 7). Land available for cropland includes protected land formally cropped, protected and unprotected pasture, protected and unprotected forest, and protected and unprotected shrub, scrub, and grasslands. Given the average number of acres used annually for maize, soybean, and wheat harvest from 2000 to 2008 in soil capability class 1 counties (Appendix Table 8), there are more than enough uncropped LCC I and II soils in class 1 counties to place *all* contemporaneous maize, soybean, and wheat production on these most productive soils without crowding out other highly productive land uses. And when you consider some LCC I and II soils are already used for cropping in soil capability class 1 counties, the capacity to "fit" all crop production in the lowest capability class counties on the most capable soils becomes even easier.

Appendix Table 7: Private acres available for cropping as of 2001 across the six Midwest states by soil class category and LCCs

S_q	LCCs 1 and 2	LCCs 3 and 4	LCCs 5 and 6	LCCs 7 and 8
1	5,694,621	12,974,740	5,634,577	5,183,282
2	4,429,804	6,405,063	2,025,908	1,371,544
3	3,663,384	3,909,285	949,454	508,868
4	3,142,765	2,027,267	566,812	298,824
5	1,915,098	639,612	171,992	114,516

Note: Data comes from Radeloff et al. (2012)

Appendix Table 8: Average number of acres used annually for harvest from 2000 to 2008 across the six Midwest states by soil class category

S_q	Maize	Soybeans	Wheat	Three Crop Total
1	1,314,666	885,613	120,113	2,320,392
2	5,575,536	5,201,073	583,584	11,360,193
3	8,295,655	8,165,158	1,114,306	17,575,119
4	10,089,931	9,804,525	1,411,379	21,305,835
5	12,843,674	11,809,598	723,452	25,376,724

Note: Data comes from USDA-NASS (2012).

Appendix Text L. Effect of marginal reclamation of cropped soils on predicted 2000 – 2008 yields

See figure 3 for the distribution of y'_{jc} (predicted annual average yield of crop *j* in county *c* from 2000 to 2008 given marginal soil reclamation) across all c in a soil capability class for each {S_q; *j*} combination. The means of these distributions are given in Appendix Text L Table 1. These means are also plotted in figure 3.

Appendix Text L Table 1: Predicted average annual yields (bu / acre) from 2000 through 2008 with marginal soil improvement

Improvement	***q* = 1 to *q* = 2**		***q* = 2 to *q* = 3**		***q* = 3 to *q* = 4**		***q* = 4 to *q* = 5**	
	Est.	**SD**	**Est.**	**SD**	**Est.**	**SD**	**Est.**	**SD**
Mean of y'_{mc} across all $c \in S_q$	140.4	7.60	141.8	13.06	145.6	12.06	155.2	10.72
Mean of y'_{sc} across all $c \in S_q$	40.0	3.21	42.5	2.69	43.7	2.35	46.3	2.31

In Appendix Text L Table 2 I give the density of the histograms in figure 3 that are at a target yield level or below. For example, to keep annual net revenues (before any reclamation costs) from a soybean acre from falling below $160 during 2000-2008, Midwestern farmers had to produce, on average, 39 bushels per acre per year (USDA-ERS 2013). Marginal reclamation would have reduced the probability of the representative acre's average annual yield from 2000-2008 falling below 39 bushels per acre by 32%, 20%, 9%, and 8% for S_1, S_2, S_3, and S_4 counties, respectively.

Appendix Text L Table 2

	Probability of 2000-2008 annual county-level average maize yield being below 140 bushels / acre			**Probability of 2000-2008 annual county-level average maize yield being below 39 bushels / acre**		
S_q	**Before reclamation**	**After reclamation**	**Difference**	**Before reclamation**	**After reclamation**	**Difference**
1	0.8558	0.4399	0.4159	0.6502	0.3333	0.3169
2	0.5986	0.3356	0.263	0.2981	0.0949	0.2032
3	0.3970	0.2532	0.1438	0.1489	0.0550	0.0939
4	0.2503	0.0875	0.1628	0.0912	0.0123	0.0789

Appendix Text M. Past Climate Change

Let GDD_{jqp} indicate the average annual *GDD* from 1950-1958 across counties in soil class *q* during *j*'s growing season.

$$GDD_{jqp} = \frac{\sum_{t=1950}^{1958} \sum_{c \in S_q} GDD_{jct}}{9 \times n(q)} \tag{V}$$

Let GDD_{jqn} indicate the average annual *GDD* from 2000-2008 across counties in soil class *q* during *j*'s growing season.

$$GDD_{jqn} = \frac{\sum_{t=2000}^{2008} \sum_{c \in S_q} GDD_{mct}}{9 \times n(q)} \tag{VI}$$

I calculate $PRECIP_{jqp}$ and $PRECIP_{jqn}$ in the same manner. All of these weather means (and mean standard deviations) are presented in Appendix Text M Table 1 and relative change between the means is presented in Appendix Text M Table 2.

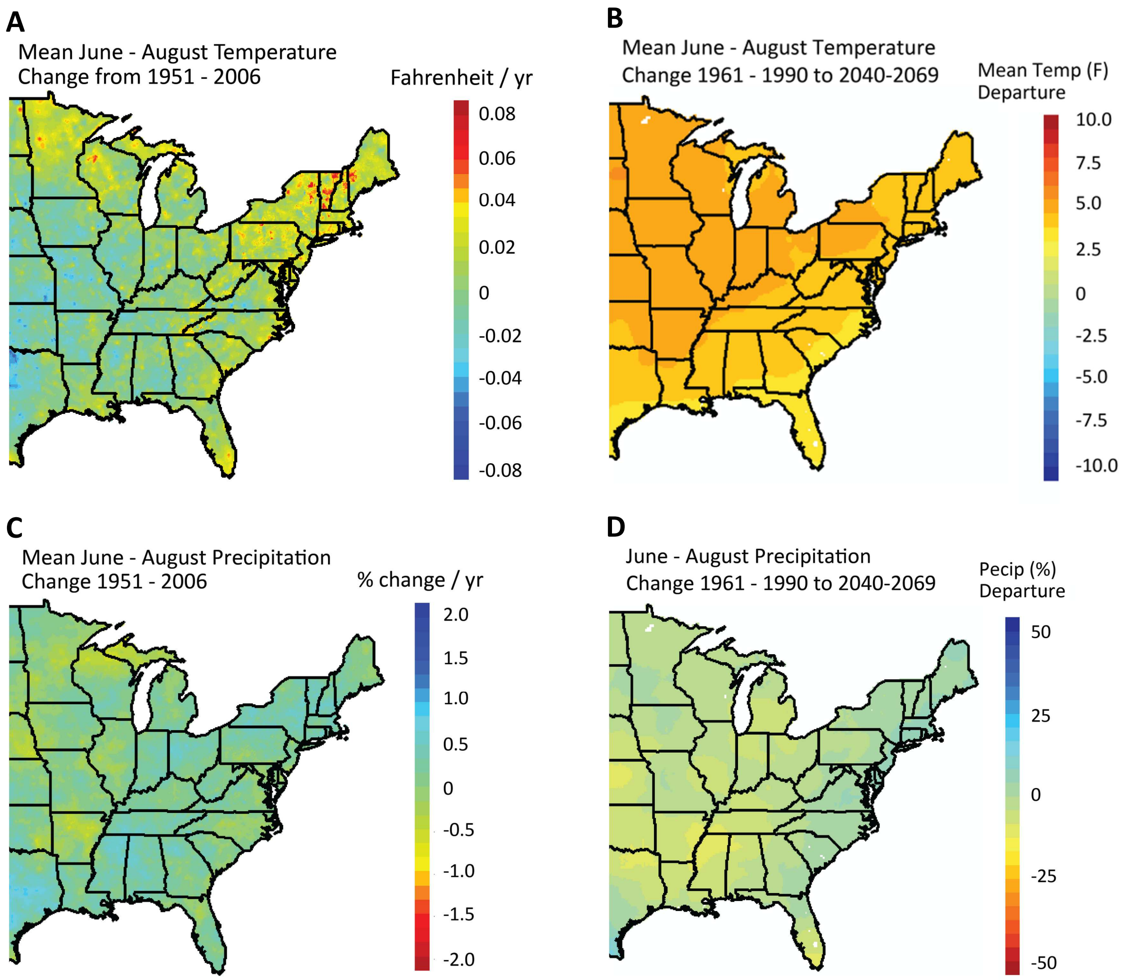
Appendix Text M Table 1: Mean *GDD* and *PRECIP* in 1950-1958 and 2000-2008

	GDD_{mqp}	GDD_{mqn}	$PRECIP_{mqp}$	$PRECIP_{mqn}$	GDD_{sqp}	GDD_{sqn}	$PRECIP_{sqp}$	$PRECIP_{sqn}$
1	2084	2178	450	499	2108	2052	410	436
Std. Dev.	389	315	99	107	269	259	102	99
2	2404	2427	464	517	2175	2196	403	440
Std. Dev.	342	329	114	111	290	276	104	98
3	2387	2391	450	512	2165	2167	391	437
Std. Dev.	308	282	113	108	267	241	103	96
4	2272	2292	444	503	2066	2082	387	431
Std. Dev.	270	245	107	103	231	210	97	93
5	2281	2301	460	521	2071	2092	403	448
Std. Dev.	213	189	110	101	188	164	101	90

Appendix Text M Table 2: Percentage change in mean *GDD* and *PRECIP* between the periods 1950-1958 and 2000-2008 by crop and soil capability class

	Maize		**Soybeans**	
S_q	**GDD** $(\%\Delta \boldsymbol{GDD_{mq}})$	**Precipitation** $(\%\Delta \boldsymbol{PRECIP_{mq}})$	**GDD** $(\%\Delta \boldsymbol{GDD_{sq}})$	**Precipitation** $(\%\Delta \boldsymbol{PRECIP_{sq}})$
1	4.5%	10.7%	-2.7%	6.4%
2	1.0%	11.5%	0.9%	9.1%
3	0.2%	14.0%	0.1%	11.7%
4	0.9%	13.2%	0.8%	11.2%
5	0.9%	13.2%	1.0%	11.4%

Appendix Text N. Maps of expected climate change



Appendix Text N Figure 1: Historic and expected changes in summer temperatures and precipitation over the Midwest. Maps produced by ClimateWizard © University of Washington and The Nature Conservancy, 2009. Base climate projections downscaled by Maurer et al. (2007)

Appendix Text O. The density of the histograms in figure 5 that are at a target yield level or below.

Appendix Text O Table 1 refers to results under the "Worst" climate change.

Appendix Text O Table 1: Probability of 2050-2058 annual average county-level yield falling being below a given yield under the "Worst" climate change scenario

	Probability of 2050-2058 annual county-level average maize yield being below 200 bushels / acre			Probability of 2000-2008 annual county-level average soybean yield being below 54 bushels / acre		
S_q	Before reclamation	After reclamation	Difference	Before reclamation	After reclamation	Difference
1	0.987	0.4754	0.5116	0.8539	0.3310	0.5229
2	0.7817	0.6088	0.1729	0.6232	0.5266	0.0966
3	0.6421	0.5693	0.0728	0.5430	0.5212	0.0218

Appendix Text O Table 2 refers to results under the "Best" climate change.

Appendix Text O Table 2: Probability of 2050-2058 annual average county-level yield falling being below a given yield under the "Best" climate change scenario

	Probability of 2050-2058 annual county-level average maize yield being below 220 bushels / acre			Probability of 2000-2008 annual county-level average maize yield being below 57 bushels / acre		
S_q	Before reclamation	After reclamation	Difference	Before reclamation	After reclamation	Difference
1	0.9968	0.3826	0.6142	0.8333	0.1672	0.6661
2	0.6667	0.3889	0.2778	0.3404	0.228	0.1124
3	0.4384	0.3242	0.1142	0.2234	0.1844	0.039

Appendix Text P. Boot-strapped estimates of model (1)

In this analysis I have to drop time and its square from the model because it is "absorbed" by the model used to conduct the group bootstrapping analysis (time is the absorbed variable in STATA's *areg* command).

Appendix Text P Table 1: Estimated bootstrap p-values of model (1) for *j* = maize, –*j* = soybeans

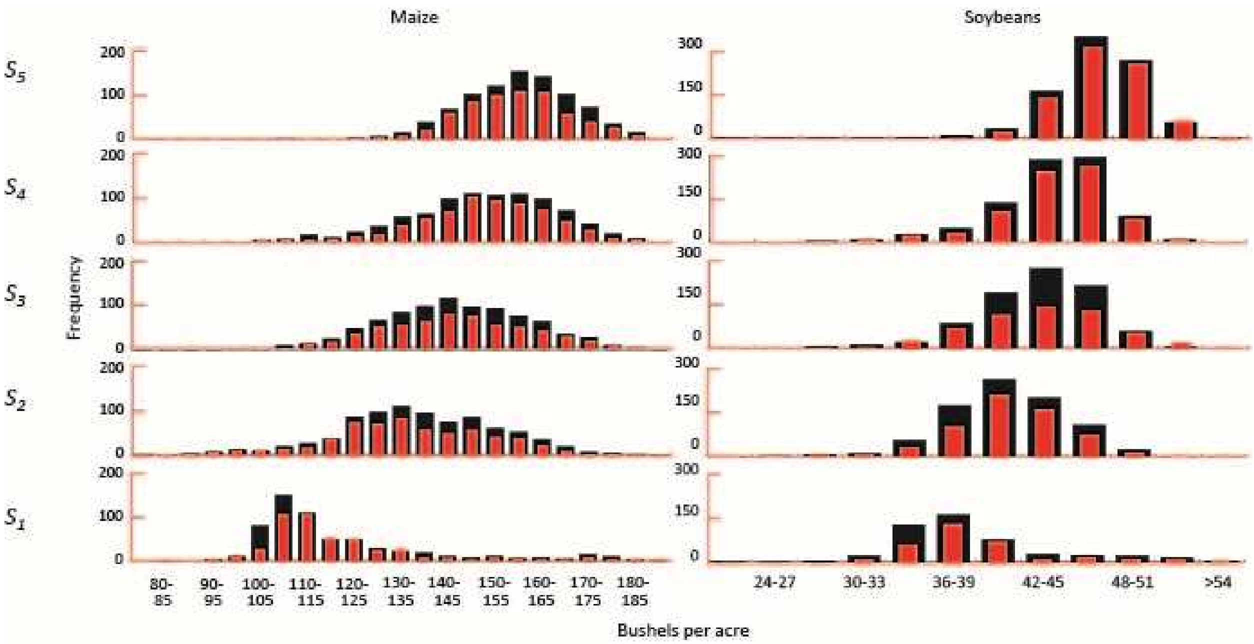
	Soil Capability Class S_q				
	1	**2**	**3**	**4**	**5**
GDD_{jct}	0.005	0.010	0.001	0.001	0.009
$PRECIP_{jct}$	0.001	0.000	0.000	0.001	0.000
GDD_{jct}^2	0.006	0.003	0.000	0.000	0.003
$PRECIP_{jct}^2$	0.003	0.000	0.000	0.003	0.000
A_m	0.000	0.000	0.000	0.000	0.000
A_s	0.000	0.003	0.000	0.001	0.001
A_w	0.095	0.031	0.096	0.968	0.030
Constant	0.012	0.160	0.032	0.021	0.051

Appendix Text P Table 2: Estimated bootstrap p-values of model (1) for *j* = soybeans, –*j* = maize

	Soil Capability Class S_q				
	1	**2**	**3**	**4**	**5**
GDD_{jct}	0.004	0.000	0.000	0.000	0.001
$PRECIP_{jct}$	0.002	0.000	0.000	0.000	0.000
GDD_{jct}^2	0.004	0.000	0.000	0.000	0.000
$PRECIP_{jct}^2$	0.011	0.000	0.000	0.000	0.000
A_m	0.000	0.000	0.000	0.000	0.000
A_s	0.021	0.518	0.118	0.120	0.013
A_w	0.029	0.440	0.098	0.478	0.035
Constant	0.077	0.000	0.000	0.000	0.010

Appendix Text Q. Chow Test results

See Appendix Text Q Figure 1 for the distribution of y_{jc} (predicted annual average yield of crop *j* in county *c* from 2000-2008) for each *j* and *q* combination only using the counties *not* dropped from *j*'s dataset due to the Chow test.



Appendix Text Q Figure 1: **Histograms of predicted 2000-2008 average annual county-level maize and soybean yields by soil class using the counties *not* dropped from *j*'s dataset due to the Chow test.** The black bars represent the distribution of county-level average yields with all counties (the same distributions as figure 2). The red bars represent the distribution of county-level average yields *only* using the counties *not* dropped from *j*'s dataset due to the Chow test. Counties with any unclassified soil area are not included. The means of these distributions are given in Appendix Text Q Table 1.

Appendix Text Q Table 1: Predicted and observed average annual yields from 2000-2008

S_q	1		2		3		4		5	
	Predicted Average Yields with All Counties									
	Est.	**SD**	**Est.**	**SD**	**Est.**	**SD**	**Est.**	**SD**	**Est.**	**SD**
y_{mq}	120.1	20.14	136.0	17.07	144.1	15.27	149.5	15.72	157.1	11.69
y_{sq}	38.8	5.11	40.9	4.09	42.9	4.05	44.02	3.64	46.9	2.83
	Predicted Average Yields with Retained Counties									
y_{mq}	119.0	16.23	132.9	15.98	142.0	13.72	148.6	12.02	156.3	10.87
y_{sq}	39.4	5.12	40.9	3.79	42.9	3.92	43.9	3.64	47.0	2.61

Appendix Text R. Comparison of my results to Schlenker and Roberts (2009)

Depending on soil capability class and modeled future, I project an 8% to 28% decline in mean maize yields and a 7% to 23% decline in mean soybean yields compared to 'no change' means by midcentury. The counties with the most marginal soils experience the lowest relative impacts from expected climate change simply because yield trend growth in these areas is already weak. The largest declines I find are in the counties with the best soil capabilities and, not coincidently, the most cropped areas. Therefore, if I found one average 2050-2058 yield for each crop across the entire six state area by weighting expected yields by expected crop area I would generate expected yield declines much closer to the 28% and 23% endpoints than the 8% and 7% endpoints. Interestingly this means my overall results are very similar to those found by Schlenker and Roberts (2009), who estimated mid-century Eastern US average maize and soybean yields using much more detailed weather data than this research. They forecast a 20 to 30% decline in annual US maize yield and a 15% to 22% decline in annual US soybean yield by midcentury compared to yields under no change.

[i] The other Midwestern states are Kansas, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin

[ii] For example, the states that are included in my study generated 67% and 67% of the region's maize for grain and soybeans in 2007.

[iii] While soil structure likely explains much of soil capability class' yield impact, I suspect that farmer investment behavior in reaction to soil capability helps explain the predicted distributions as well. It stands to reason that farmers would more intensively manage crops on more capable soils because of an expected higher rate of return on production investment and lower risks of very low yield or outright crop failure (recall that I found that areas with more capable soils have a lower crop failure rate, all else equal). Therefore, if greater yields on more capable soils are partly explained by more intensive management practices then cropping on more capable soils generate two types of benefits for society. The first benefit is more capable soil's innate capacity to produce better yields, all else equal. The second benefit comes from more capable soil's ability to cajole risk adverse farmers into investing more time and expense into crop production.

[iv] Another pathway for better use of Midwestern soil resources is to reallocate maize and soybean production from the most marginal soils to the most capable soils. As of 2001 the six modeled states had 18.85 million acres of the most capable soils (LCCs I and II) that were not in cropland but reasonably could have been (see Appendix Text K). By reasonably available I mean that land in question, including protected cropped land, protected and unprotected pasture, protected and unprotected forest, and protected and unprotected range, presumably could have been prepared for cropping at a reasonable cost. However, such widespread transformation of the best soils currently in alternative uses would generate extensive environmental destruction. Here I am interested in proposing solutions to 21st century agriculture problems that will not involve substantial sod busting and clearing a multitude of tree stands.

[v] Of course soil reclamation may have led farmers to change the relative allocation of crops across the Midwest from 2000-2008 and the representative acre from class S_q would then be different than the observed allocation.

[vi] Recall that I also found that marginal reclamation has also been associated with reductions in the risk of crop failure; the ultimate bad outcome.

[vii] Again, maize and soybean crop production could use it soil resources more intensively in the future by shifting marginal crop production to the best soils. However, given society's other desires for scarce land (urban and transportation uses; forests for aesthetic and recreation purposes, as a sink for carbon, and habitat for animals; pasture for livestock, etc.) it seems reasonable to assume that the location of cropped lands will not change drastically over the next 50 years. In fact, a recent analysis by Lawler et al. (2013) suggests that if commodity prices from the late 2000s continue into the future additional cropland will be added to Midwestern landscape primarily in the counties with the least capable soils.

[viii] Mr. Dobos continues, "There are a couple of "reclamation" projects I can think of. First, I know that in California, some hardpan soils are ripped with huge subsoilers and pans are broken to allow root and water penetration. The additional plant available water could change a soil from [LCC] 4 to [LCC] 2 in some situations, but I do not have any data for that. Another "reclamation" project might be good, old fashioned artificial drainage. This can easily move a soil from [LCC 4 to LCC 2], like the Drummer or Muscatine soils of the Midwest. The project would need to be extensive enough to be recognized as a significant management practice in the soil survey report."

[ix] Of course I cannot rule out other omitted reasons for a structural shift compared to its cohort such as a county's unique adoption of a specific crop management technique, a specific cultivar, etc.

[x] For example, consider S_3. Some of its members may have actually been in S_2 in the 1950s and 1960s and then marginal reclamation bumped them up by the time the soil map was made beginning in the 1980s. All else equal these counties will bias $\bar{Y}_{js_3(c)t}$ downward in the earlier years. However, the soil capability in a county can decline over time as well. Therefore, some of S_3's members may have actually been in S_4 in the 1950s and 1960s and then degradation dropped them down by the time the soil map was made beginning in the 1980s. All else equal, these counties will bias $\bar{Y}_{js_3(c)t}$ upward in the earlier years. These countervailing biases could help keep $\bar{Y}_{js_3(c)t}$ rather insensitive to soil capability changes over time.

[xi] Global population in 2013 is 7,095,218,000. Population by 2050 is expected to be 9,383,148,000 for a growth rate of 32%. See http://www.census.gov/population/international/data/idb/informationGateway.php