Adjustment Costs from Environmental Change Induced by Incomplete Information and Learning

by

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ABSTRACT

The paper begins with the problem of a firm subject to random productivity shocks drawn from a particular distribution. We are concerned with the case whereby the distribution of the shocks changes without the knowledge of the firm. Over time the firm learns about the nature and extent of the change in the distribution of the shock and adjusts, incurring adjustment costs in the process. The long run loss in profits (±) due to the shift in the distribution we term the adaptation costs. The transitory profit loss, incurred while the firm is learning about the distribution shift, is termed the adjustment cost. The theory is developed and then applied to the problem of measuring adaptation and adjustment costs in the face of unanticipated and imperfectly observed climate change in agriculture. The empirical part of the paper involves estimating a supply function for corn that depends on actual weather realizations and expected weather, using county level data for the US. We then simulate the effect of an unobserved climate shock, where learning about the climate shock is by observing the weather and updating prior knowledge using Bayes Rule.

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I. INTRODUCTION

One of the most important issues in the climate change debate is the quantification of the costs of adjustment and adaptation that may be associated with a change in the climate. If the sea level is to rise, what are the costs of moving coastal cities inland? If the midwest warms, how will agriculture adapt and what will be the costs? It is important to distinguish between the long-run effects and the short-run effects. In the case of agriculture, the long-run effect involves changing land use and cropping methods; the losses associated with such a change may be large or small and may be either positive or negative. A warmer Midwest may produce more, once agriculture has adjusted. In the literature, adaptation refers to the long-run changes that are taken in response to climate change. The issue of the ultimate cost of adapting to climate change has been the subject of a number of papers.[1]

A second issue however, is the short-run effects of climate change. If we are caught off-guard or even unawares, costs will be incurred in adjusting to long-run equilibrium. These adjustment costs are the focus of this paper. They have received very little attention in the literature. We are interested in the transitory costs of adjusting from one long-run equilibrium (the current climate) to another long-run equilibrium (a changed climate). This is not unlike the question in the investment literature that arises when relative prices change unexpectedly and firms must adjust the level of quasi-fixed factors such as capital. While the long-run equilibrium effects of the relative price change may be modest, the process of adjustment may be significant and protracted. In the case of climate change, the short-run is unlikely to be very short.

[1] See the discussion of adaptation in the National Academy of Sciences (1992) study on climate change. Schimmelpfennig et al (1996) have addressed adaptation in agriculture.

We divide adjustment costs into two basic components. One is related to the cost of adjustment of quasi-fixed factors, as mentioned in the previous paragraph, in the context of shifting relative prices. But shocks can be physical as well as monetary. If the sea level rises unexpectedly, there are costs of adjusting to that rise. Buildings must be moved, and infrastructure abandoned and reconstructed. This is a problem of fixed capital, capital that cannot easily be moved, modified or adjusted. The slower the adjustment need be, the lower the cost. In other sectors of the economy, capital fixity is less of an issue; for instance, in agriculture, if the climate changes, crops can be relatively easily changed and the amount of capital that is made obsolete is probably minimal.

Knowledge and information also play a key role in the magnitude of adjustment costs. In agriculture, a farmer may observe several consecutive hot summers but rationally attribute the apparent increase in hot summers to random variation in the weather. Eventually the farmer realizes the climate has changed; in the meantime there are costs associated with "errors" in input and crop choice. On the other hand, if the climate change is anticipated or known to the farmer, then the adjustment costs are lower or even zero.

There are two purposes of this paper. One is to provide a theoretical structure for viewing adjustment and adaptation in the context of environmental change, specifically climate change. The second purpose of the paper is to apply this theoretical structure; in particular, we consider agriculture and examine the costs of adjustment in US corn production.

In the next section of the paper we provide background information, both on the cost of adjustment in the context of the adjustment of quasi-fixed factors as well as the literature on production in an environment of uncertainty. In the subsequent section, we present a theoretical model of the adaptation and adjustment costs of a neoclassical firm subject to random shocks and an imperfectly observed change in the distribution of these shocks. We then apply this model to US agriculture, measuring the structure of production as a function of expected climate and realized climate (weather). We conclude by hypothesizing Bayesian learning about an unobserved climate change and estimate the output effects for a segment of agriculture (corn) associated with this learning process.

II. BACKGROUND

There are two issues that are of concern in this paper. One concerns how uncertainty and unanticipated shocks affect production, particularly in agriculture (the application considered in this paper). The question is, if farmers know the climate has changed, how do they respond and what is the welfare effect of this response? This is adaptation. The other issue of concern has to do with the transition to a different climate. This involves a variety of issues, including learning about the climate and adjusting input use in response to changed conditions. This is adjustment.

A. Adapting to Climate Change

A number of authors have considered the effect of climate change on agriculture. Adams et al (1990) and Rosenzweig et al (1994) are prominent examples of the use of agricultural process models (including crop growth models) to measure the effect on crop yields of climate change.[2] These models are typically physiological with limited scope for endogenous farmer behavioral response to climate change. Typically, adaptation and adjustment are absent or exogenous.[3]

[2] Agricultural process models are akin to activity analysis models in production. Complete enumeration of all possible technological options is desired; relative prices are used to determine an efficient technology choice (eg, see Adams et al, 1990).

[3] There are fewer econometric analyses of the effect of climate change on agriculture. Perrin and Smith (1990) investigate the effect of weather on several crops in North Carolina and then use results of climate models to estimate the effect on crops of climate change. Hansen (1991) estimates the effect of weather and climate on corn yield and then postulates the effect of a change in climate. Some studies in agricultural economics and agronomy focus more directly on the weather effect (Kaylen et al, 1992; Thompson, 1986; Wescott, 1989). These models approach the problem after the production decisions have been made, only considering the effect of actual weather realizations on yield. Typically the weather data is transformed into some measure of deviation from expected weather. The underlying idea is that the effect of normal weather (represented by climatic expectations) is captured in the farmer's cropping practices, but that unusual weather will have an impact of yield.

Some crop growth models allow a certain amount of farmer adaptation to climate change. For instance, Kaiser et al (1993) use a simulation model to forecast a century of effects from a gradual change in the climate. Their model assumes farmers choose which variety of crop would have done best in the previous (simulated) decade. In this way, some adaptation over time is represented in their model. This results in considerably less loss from a doubling of carbon dioxide concentrations (Schimmelpfennig et al, 1996).

Hansen (1991) suggests that the use of crop growth models (which must enumerate substitution possibilities) may miss some of the substitution opportunities available to farmers. He estimates a cross-sectional model of corn production in the US where expected climate (July mean temperature and precipitation) as well as realized weather (among other factors) are used to explain cross-sectional variations in corn yield. His results for a temperature increase are mixed (as might be expected), showing yield increases in some climates and yield decreases in others.

Mendelsohn et al (1993, 1994) and Johnson and Haigh (1970) go even further and assume *complete* adaptation, both in crops and input decisions. Figure 1 (adapted from Mendelsohn et al, 1994) illustrates this point. Shown in the figure are response curves for multiple uses of land as a function of the climate (simplistically represented by average temperature). These reflect the value of the product (net of costs) of the land after full equilibration to a climate change. The upper locus of points, shown as a heavier line, is the maximum value of the land. A loss from climate change would be the difference in this value associated with a changed climate, taking into account crop substitution and other changes in land use. Allowing this substitution to occur but keeping the crop the same, results in a more significant loss from climate change, as illustrated by the points along the wheat curve in the Figure (such as points C or F). Keeping the crop fixed as well as all other practices of the farmer results in points interior to the crop-specific curve in the figure, such as point G -- the "dumb farmer" point.

From this perspective, Mendelsohn et al (1993, 1994) have measured the differences in land values across the US, inferring that land value differences are due to endowed soil quality and climate.[4] This allows the authors to infer the value of different climates. Using this approach, they infer a very small effect (possibly positive, possibly negative) on US agriculture from climate change.[5] In effect, the Mendelsohn et al papers establish a lower bound on the cost of climate change on agriculture, corresponding to perfect and instantaneous adaptation.

McFadden (1983) has a different perspective, focusing on how a farmer (or other agent) may change its behavior based on uncertainty about climate change (or even weather variability). In essence, if the farmer feels there is a possibility of climate change, he may adopt more robust practices (e.g., irrigation) that perform relatively well over a range of weather or climates, sacrificing a bit relative to the case of perfect knowledge about the weather.

B. Adjusting to Climate Change.

The literature on adjustment costs in agriculture from climate change is very sparse. The only paper of which we are aware is Kaiser et al (1993). As was mentioned in the previous section, they simulate the effect of gradual warming by allowing crop variety choice to gradually change over time, based on best practice in the previous time period (decade).

There are two related literatures that are relevant. One concerns the rate of adoption of new technologies. As Riley (1995) points out, historically agriculture has been relatively slow to adapt to innovation, ranging from new crops to new technologies. There is some literature on the process

[4] Interestingly, Johnson and Haigh (1970) examined the value of climate using a very similar approach, though from the point of view of valuing intentional and supposedly beneficial weather modification.
[5] The climate change they consider is a uniform 5°F (2.8°C) warming accompanied by a uniform 8% precipitation increase. A similar analysis of Russian agriculture found an output gain from the same amount of climate change (Kolstad et al, 1998).

of adopting new technology, focusing primarily on learning on the part of farmers in the context of incomplete information (e.g., Fischer et al, 1996; Ellison and Fudenberg, 1993). Farmers start out with a very diffuse prior on the usefulness of the new technology; over time they observe how well (or poorly) others do with the technology and from that experience, revise their priors. Bayesian learning is the starting point for these models although as Fischer et al (1996) point out, Bayesian models tend to overstate learning rates in some cases.

The literature on adjusting the optimal level of capital in response to changed relative prices (Slade et al, 1993) emphasizes the cost of rapidly adjusting the capital stock. If, for instance, energy prices rise rapidly and call for a substitution of capital for energy in production, this shift cannot be made rapidly. Explicitly recognizing the cost of adjustment makes the path of adjustment of the capital stock the result on an intertemporal tradeoff between adjustment costs and expenditures on other factors. It would not appear that this literature has much to offer in the agricultural context where capital (other than land) is relatively easy to change over time.

III ADJUSTMENT COSTS WITH UNOBSERVED CLIMATE CHANGE

Here we consider a neoclassical firm (a farm is what we have in mind) where the production function is subject to stochastic shocks. There are a number of input decisions the firm must make, some before the shock is realized, some after. The size of the shock in conjunction with input decisions determines the magnitude of output. An example is a farm which makes planting decisions in the spring based on expected weather (including deciding on how much land to plant). Output in the fall will be determined by these earlier input decisions and the weather that occurs over the summer. Thus output is a function of anticipated weather (climate) and realized weather, as well as other exogenous factors, such as soil characteristics, and the use of conventional inputs into production. This is an abstraction of a process where some input decisions are made prior to the resolution of uncertainty; other input decisions may be made after some uncertainty has been resolved; still other input decisions may be made after all uncertainty has been resolved.

Now suppose the climate changes but the farmer observes only the realized weather, not the underlying distribution (the climate) generating the weather. Over time the farmer slowly updates her prior on the anticipated weather, based on observed weather realizations. While she is learning, decisions are suboptimal, relative to the case of perfect information. The loss of output and profits constitutes the adjustment cost.

A. Stochastic Production

We consider a stylized model of a firm subject to stochastic shocks. In developing the model, we avoid excessive detail related to a particular sector, such as agriculture. That detail will be added later in the paper when we present an empirical application of our model.[6]

The model we consider involves two time periods and a firm. Production depends on input choice as well as a stochastic shock. This could be a physical shock to the production technology (which is how we consider it) or a price shock. The shock occurs between the first and second time periods. Thus the magnitude of the shock is uncertain in the first time period but known in the second time period. Inputs, X, are chosen in the first time period. Output is determined in the second time period. Let W be the random shock, distributed as $W \sim g(\omega)$. The density function, g, as well as the parameters of the distribution, ω, are fully known in both the first and second time periods. Production is determined by the realized shock only, not expectations:

$$Y = f(X,W) \tag{1}$$

This is an *ex post* production relation in the sense that the value of W is not known *ex ante*, when input decisions must be made. (This is consistent with the framework of Pope and Chavas, 1994.) The firm faces prices for output, p_Y, and inputs, p_X. We assume these are not uncertain nor are they affected by the shock.[7]

We characterize production at two different points in time: prior to resolution of the uncertainty (*ex ante*) and after resolution of the uncertainty (*ex post*) since demand for X is an *ex ante* demand and the supply of Y is *ex post*. Thus we generate *ex ante* profit, supply and factor demand equations, which depend on information available in the first time period. We also generate *ex post* profit and supply equations, which depend on information available in time period 2 and decisions made in the first time period.

<u>1. *Ex Ante* Profits, Factor Choice and Output</u> Prior to the realization of the shock, the <u>expected</u> profits, *ex ante*, are defined as

$$\Pi^{**}(p_X,p_Y, \omega) = \max_X \; E_\omega \{ p_Y f [X,W] - p_X X \} \tag{2}$$

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[6] Other authors have considered the theory of the firm under input and output price uncertainty. See Sandmo (1971), Batra and Ullah (1974) and Blair (1974). A more recent application to international trade but in the spirit of firm choice under uncertainty can be found in Wolak and Kolstad (1991).

[7] One might expect there to be uncertainty in the price of output, particularly if there is a time lapse between the first period and the ultimate sale of product. Furthermore, one might expect the output price to be correlated with the shock. This latter point may or may not be true. In the case of agriculture, the futures price is the expected price at harvest, which will be correlated with weather over the entire market. Thus the farmer should have expectations about her own weather and market-wide weather. These two may well be uncorrelated. We are ignoring these issues, which amounts to the producer entering into a contract to deliver output (the quantity of which is uncertain) at a agreed-upon price.

where E_ω is the expectations operator over the random variable W, distributed as $g(\omega)$. Associated with the profit function in Eqn. (2) is a factor demand equation for factor X, chosen in the first period: $X(p_X, p_Y, \omega)$.

2. *Ex Post* Profits and Output. *Ex post* profits are the profits as measured in the second period, after the shock has been realized. Define *ex post* profits as

$$\Pi^*(p_X, p_Y, W, \omega) \quad = \quad p_Y\, f[X(p_X, p_Y, \omega), W] - p_X\, X(p_X, p_Y, \omega) \tag{3}$$

In conjunction with Eqn. (3), there is an *ex post* output supply equation, $Y^*(p_X, p_Y, W, \omega)$.

Note that the basic difference between the ex ante and ex post profit functions is the knowledge of the realization of the random shock. Clearly,

$$\Pi^{**}(p_X, p_Y, \omega) = E_\omega \{\Pi^*(p_X, p_Y, W, \omega)\} \tag{4}$$

B. Unanticipated and Unobserved Change in Distribution of Shocks

Now consider the case where the distribution of the shock changes but that change is both unanticipated and imperfectly observed by the firm. Over several production cycles the firm observes realized shocks and slowly updates priors on the distribution of the shocks.

For instance suppose in the case of agriculture, that the mean July temperature has risen by 2^o C. How will this fact become known to farmers? Over several years, farmers observe the July temperature and gradually revise their estimate of the mean of that variable. Until they become completely informed of the new mean temperature, they will make input "mistakes" and thus suffer output and profit losses, relative to being perfectly informed.

Figure 1 illustrates this. Earlier we interpreted the horizontal axis as climate; we now view the Figure as showing the net value of output as a function of realized weather. Assume, somewhat artificially, that the farmer can only choose what kind of crop to plant; there are no other adjustments she can make (such as seed variety or timing). This is clearly an oversimplification but will suffice for our purposes. As drawn, wheat is ideal if the anticipated weather is T_1 whereas corn is ideal if the anticipated weather is T_2. With different assumptions about mean weather (climate), farmers will choose different crops.

We start with the assumption that the average temperature is T_1. Now suppose the climate has changed so that the mean temperature is now T_2. In this case, corn should be the crop of choice. If the climate change is unobserved, the farmer continues to plan wheat. If the weather realization is T_2, then the value of output will be at point F, not D where it could be. This is a loss associated with incomplete information, the adjustment cost. This process can be made more precise.

1. Adaptation and Adjustment Costs

Suppose ω_o is the firm's initial subjective estimate of the parameters of the distribution of the random shock at any point in time, based on the historical record. Now suppose the distribution changes so that $\hat{\omega}$ is the new true parameter vector on the distribution of the shock, though the producer does not observe this change. Let $\omega(t)$ be the firm's subjective assessment of the true parameters of the distribution at any point in time, t. Each year the realized shock, W(t), will be drawn from the distribution $g(\hat{\omega})$. Assume the producer observes W(t) and updates her prior $\omega(t-1)$ to yield the posterior, $\omega(t)$. How this updating is done is another question, which we turn to later. We would expect that $\lim_{t \to \infty} \omega(t) = \hat{\omega}$. Output in any given year will be determined by the *ex post* supply function, $Y^*(p_X, p_Y, W, \omega(t))$, where W is the realized shock in year t, drawn from $g(\hat{\omega})$. This can be compared to the supply associated with perfect information about the distribution of the shock, $Y^*(p_X, p_Y, W, \hat{\omega})$. Corresponding profit functions are $\Pi^*(p_X, p_Y, W, \omega(t))$ and $\Pi^*(p_X, p_Y, W, \hat{\omega})$. There are two losses, one the adjustment cost due to incomplete knowledge of the new distribution and another loss, the adaptation loss, due to the effect of the changed distribution on production. The per period adaptation cost is quite simply

$$L_{ADP}(\hat{\omega}) = \Pi^{**}[p_x, p_Y, \hat{\omega}] - \Pi^{**}[p_x, p_Y, \omega] \tag{5}$$

whereas the per period adjustment cost is

$$\begin{aligned} L_{ADJ}(\hat{\omega}, \omega(t)) &= E_{\hat{\omega}}\{\Pi^*[p_X, p_Y, W, \hat{\omega}] - \Pi^*[p_X, p_Y, W, \omega(t)]\}. \qquad (6a) \\ &= \Pi^{**}[p_X, p_Y, \hat{\omega}] - E_{\hat{\omega}}\{\Pi^*[p_X, p_Y, W, \omega(t)]\} \end{aligned}$$

Let ϕ be the discount rate; then the total adjustment cost is

$$NL_{ADJ}(\hat{\omega}) = \sum_t (1+\phi)^{-t} L_{ADJ}(\hat{\omega}, \omega(t)) \tag{6b}$$

Eqn. (5) indicates how much better off or worse off the firm is as a result of the shift in the distribution, leaving aside the question of incomplete information. Eqn. (6a) defines the expected annual loss in profit due to incomplete information (there would be an analogous loss in output) and Eqn. (6b) converts a stream of these losses back to the present using the discount rate ϕ. Both depend on the ultimate distribution, $\hat{\omega}$, as well as the path of knowledge about the distribution, $\omega(t)$.

It is important to point out that the losses in Eqn. (5-6) are not the net welfare losses to the economy since we are focusing on a firm only. We are assuming that these changes are occuring in isolation, that there are no price effects (prices are constant). To extend this to the market, we would have to take into consideration the effect of the shock on prices, the effect of the change in the distribution on prices, but not only for the product in question but other products whose demand depends on the price of substitutes and complements. In a dynamic context, we would have to take into account the effect on technical change. A welfare measure of the consequences of this learning would involve the changes in surplus accruing to all producers and consumers. If we were examining a farm, with weather the shock and climate the distribution, then we would need to take into account the full set of farm outputs, substitutes and complements for those outputs, effects of weather and climate on prices, possibly worldwide, the effect of these changes on technology, and the distribution of surplus between producers and consumers.

2. Learning

How will $\omega(t)$ evolve over time? In the simplest case, assume that W is a scalar and that we (including the producer) know that it is drawn annually from a normal, $N(\omega,1/\rho)$, distribution. Let us assume we know ρ but do not know ω, at least not perfectly (the case of not knowing either is a simple extension). At time t, we start with a prior on ω, ω_t, which we know with some precision, p_t (ie, a variance of $1/p_t$). Over time we observe draws (realizations) of W, W_t, drawn from the distribution of whose mean we are not quite sure. Bayes' rule tells us how to efficiently update the priors we have on the mean and precision of that estimate (DeGroot, 1970):

$$\omega_{t+1} = \{\omega_t p_t + \rho W_t\} / \{p_t + \rho\} \tag{7a}$$

$$p_{t+1} = p_t + \rho \qquad (7b)$$

If a change in the distribution occurs, changing the process which generates the shock, then the producer will slowly update her prior on the random process according to eqn. (7). How long will this take? Suppose at time zero, the mean of the shock changes to $\hat{\omega}$. Assume *a priori* that the shock is distributed $N(\omega_o, 1/\rho)$. Further, the variance on our estimate of ω_o is $1/p_o$. Then in expectation, after n years, we expect (DeGroot, 1970) the updated mean shock to be given by

$$\omega_n = \{\omega_o p_o + \rho\, n\, \hat{\omega}\} / \{p_t + n\, \rho\} \qquad (8)$$

For $\hat{\omega}$ to dominate the first term in braces, either n (or ρ) must be large or p_o (the initial precision on ω_o) must be small. One should expect this to be relatively slow moving. Priors are built on many decades of information; one should not expect that experience to be thrown out without many decades of contrary information.

Although Bayesian updating is the efficient way to process this new information, it is not an altogether satisfactory way of representing learning. One "problem" is that a century of past observations will tend to cause the prior to change very slowly, even when confronted with radically different new information. For instance, in the case of agriculture, anecdotal evidence suggests that some farmers are more myopic, weighing recent information more than is efficient (Weber and Sonka, 1994; Smit et al, forthcoming). Secondly, the Bayesian process requires a structural model that includes as many determinants of the observed variable as possible. For instance, eqn. (7) assumed that the distribution of shocks was fixed, but with unknown mean and variance. If we posit a more complex process responsible for the change in the distribution, we will need a different structural model. A different structural model may give quantitatively different results on learning.

IV. AN EMPIRICAL ESTIMATE OF ADJUSTMENT COSTS FOR CORN

In implementing the theory of the previous section, we will focus on corn in the U.S. As articulated earlier in this paper, to completely characterize adjustment and adaptation, it is important to capture farmer responses with regard to single crops as well as substitution of one crop for another. Thus focusing on one crop -- corn -- is clearly only an intermediate step, one which will inevitably overstate adjustment costs. For example, output losses in corn may be made up by output gains in soybeans. Furthermore, we will be ignoring the demand side of the market; thus price changes as well as surplus changes for the consumer will be ignored. Technological change will also be assumed to be unchanged. These assumptions about price and technology are really only appropriate when climate change only affects a small part of the market, a questionable assumption.

There is some literature to draw upon in for guidance in estimating how weather, climate and other factors affect corn output. Kaufman and Snell (1997) estimate a model of how weather, climate and economic factors influence yield and estimate their model on a cross-section of US counties for the 1969-87 period. This work is important in identifying what factors are most important in determining yield. Several other authors (Thompson, 1986; Kaylen et al, 1992; Hansen, 1991; Westcott, 1989) have econometrically estimated yield equations for US corn, typically on the basis of county data. This work is also useful in identifying the most important factors to use in explaining corn output.

The approach we used is based on Nerlove (1958). The idea is to separate the land or acreage choice decision from decisions on other inputs. We then estimate a land demand equation and a conditional output equation, conditional on the amount of land used. We assume that land is chosen at the beginning of the season before weather has been realized. Other inputs are chosen in the summer, after weather has been realized. This then determines output, which will be a function of prices and weather, as well as other factors that influence output. Basically we estimate an *ex ante* demand equation for acres planted to corn separately from a restricted supply equation for corn output, conditional on acres planted to corn. The estimation is conducted over a pooled time series-cross section of US counties. Because not all counties produce corn, we estimate output and acreage equations only over counties that produce corn, adjusting the estimation for sample selection bias.

A. The Model.

One way to implement eqn. (5-6), in terms of output loss (rather than profit loss), is to estimate the *ex post* supply function for corn.[8] Following the development in the previous section, we model supply as a two-step process. The two steps involve first estimating a demand function for land, depending on prices and climate (and other exogenous variables), but not the weather realization (since the planting decision is made in the spring).[9] The second step is to estimate the restricted supply function for corn, conditional on the amount of land chosen. This is the output of corn, expressed as a function of land used, prices, climate (and other exogenous variables) and weather.

The intuitive description of farmer behavior is consistent with this model. In the spring, the farmers in a county decide on the amount of land planted to corn in the county. This is based on climate in the county (ω: April and July average temperature and average precipitation, the

[8] We examine output loss rather than profit loss because we do not have observations on cost nor other outputs of the farm. This assumption will tend to overstate the loss or gain from an unobserved change in climate.

[9] This is somewhat of an oversimplification. Some weather is realized in the spring prior to planting; farmers see how wet the spring is, they see soil temperature, they see how late they actually are able to plant to to soil wetness.

standard errors of these values and the covariance between temperature and precipitation in July), the price of variable inputs (the Commodity Credit Corporation loan rate and an input price index -- p_X), the futures price of corn and competing crops (wheat and soybeans), soil characteristics and geographic information (latitude, longitude, elevation and soil) and demographic characteristics (county size, total income of the county and total population of the county). Technical change, represented by a time trend, may also play a role. Collect these exogenous variables into a matrix **R**, defined over the panel. Thus the land planted to corn in county i in time period t, represented as the vector **L**, is given by:

$$\mathbf{L} = \mathbf{f}(\mathbf{R}) + \xi \tag{9}$$

where ξ is an error term which we would expect to exhibit spatial and temporal autocorrelation. We would also expect eqn. (9) to be homogeneous of degree zero in prices.

The second step decision is to choose levels of variable inputs, given the amount of land planted to corn. This is the restricted demand for variable inputs, conditioned on the amount of land. The exogenous variables are the same as for Eqn. (9) except that we omit the capital price (CCC loan rate), the prices of substitutes and demographic variables; we add weather variables (April and July temperature and precipitation). We assume that the price of other crops does not affect the input decisions, once land has been committed. *Ex post* corn output (Y) will thus be determined by prices of corn and inputs, acreage planted to corn (L), climate, realized weather, soil and geographic characteristics and a time trend to reflect technological change. To reduce co-linearity between weather and climate, weather is expressed as normalized deviation from expected weather -- a z-score. Collect these exogenous variables over the panel into the matrix **S**. Output in county i, time period t, defined as Y_{it}, is given by

$$\mathbf{Y} = \mathbf{g}(\mathbf{S}) + \zeta \tag{10}$$

where ζ is an error term which may have similar properties as ξ in eqn. (9). Eqn. (10) should be homogeneous of degree zero in prices. Constant returns to scale would imply Eqn. (10) is homogeneous of degree one in acreage planted to corn.

B. Estimation

Econometrically, there are several issues. Many counties have no corn planted. Those counties that do plant corn are not a random sample of counties, but rather counties in which corn does well. This sample selection can bias the OLS estimates of eqn. (9) and (10). There are two ways to deal with this. One is to correct for sample selection using, for example, Heckman's two-step procedure with a sample selection equation (Greene, 1990). Alternatively, we can apply a Tobit procedure, recognizing that acreage and output are truncated at zero (Maddala, 1983). Either method will have problems when spatial autocorrelation exists in the data (which is likely here), but these problems have substantially less effect for the first method, which we follow here.[10]

To be more specific, we correct our estimation for spatial and temporal autocorrelation, heteroskedasticity and sample selection. First consider sample selection. We adopt a method of

[10] In the Tobit, the truncation effect must simultaneously be estimated with the autocorrelation coefficients. This creates problems because of the presence of zero observations and lags. This causes the autocorrelation parameters to be overestimated because of the use of zeros for lagged variables that should be negative but are truncated. In the sample selection approach, the sample selection bias is first estimated, without correcting for autocorrelation. The results of this esimate are consistent but not efficient. These estimates are used to generate the sample selection correction which is used in the second stage. The acreage and ouput equations are then estimated, correcting for both autocorrelation and sample selection.

Heckman (1979), as articulated in Greene (1990), to make this correction. Let y_{it} be our censored observations of the dependent variable and z_{it} an indicator of whether y_{it} is observed to be positive. Recall that we are estimating a panel data set, a pooled time-series, cross-section. The cross-section has N members (indexed by i) and there are T time periods (indexed by t) for a total number of observations of NT. An OLS regression of **y** on independent variables will be biased due to the fact that **y** is truncated (we do not observe negative y_{it}). The expectation of the error conditional on y_{it} being positive, is not zero. This can be corrected by augmenting the independent variables by a factor proportional to the conditional expectation of the error.

Define **z***, which is unobserved, as a linear function of the dependent variables, **V**:

$$\mathbf{z^*} = \mathbf{V}\gamma + \mathbf{u} \tag{11}$$

We do observe **z**, which is determined by **z***:

$$z_{it} = \begin{cases} 1 & \text{if } z^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

In Eqn. (12), **z** is the *selection variable* for observing **z***. Similarly, the truncated dependent variable in which we are primarily interested is observed only when $z_{it} = 1$.

In the first stage of the Heckman correction for sample selection, we estimate Eqn (11-12) as a probit[11]. (In estimating the probit, we use the same exogenous variables as the acreage equation, Eqn. 9.) Using the estimated probit, we calculate an auxillary variable, λ_{it}, for every member of the

[11] In estimating the probit, no attempt is made to correct for heteroskedasticity or autocorrelation, both of which may be present.

panel. This variable represents the expectation of the residual, conditional on corn production being greater than zero. We then augment the exogenous variables (**V**) explaining the dependent variable, **y**. Let the augmented matrix of exogenous variables, including λ, be **X**. This corrects for sample selection.

Consider now the corrections for autocorrelation. For a time period t, the cross-sectional equation of N observations is

$$\mathbf{y}_t = \mathbf{X}_t \beta + \varepsilon_t \tag{13}$$

Spatial autocorrelation implies the error structure

$$\varepsilon_t = \delta \mathbf{W} \varepsilon_t + \eta_t \tag{14}$$

where **W** is a NxN weighting matrix. We assume that the ijth element of **W** is $1/d_{ij}$ where d_{ij} is the distance in miles between counties i and j. For distances greater than 500 miles, we assume the weight is zero. This can be rewritten in terms of the entire panel as

$$\varepsilon = \delta \mathbf{M} \varepsilon + \eta \tag{15}$$

where the NT x NT matrix $\mathbf{M} = \mathbf{I} \otimes \mathbf{W}$, using the TxT matrix **I**.

Temporal autocorrelation of η can similarly be represented by

$$\eta = \rho \mathbf{T} \eta + \mathbf{v} \tag{16}$$

where $\mathbf{v}$ ~ Normal ($\mathbf{0}$, Ω) with Ω diagonal. Eqn. (15) and (16) can be combined into

$$\mathbf{A}\,\varepsilon = \mathbf{v} \qquad \text{where } \mathbf{A} = (\mathbf{I} - \rho\mathbf{T})\,(\mathbf{I} - \delta\mathbf{M}) = (\mathbf{I} - \rho\mathbf{T} - \delta\mathbf{M}) \tag{17}$$

We can "pre-whiten" the variables in Eqn. 13 by pre-multiplying by **A**. Define

$$\mathbf{y^*} = \mathbf{Ay} \tag{18a}$$

$$\mathbf{X^*} = \mathbf{AX} \tag{18b}$$

$$\varepsilon\mathbf{^*} = \mathbf{A}\varepsilon \tag{18c}$$

where ε^*_{it} ~ Normal (0, σ_{it}^2). Errors may be heteroskedastic, having different variances over the cross-section. We assume

$$\sigma_{it}^2 = \mathbf{Z}_{it}\,\upsilon \tag{19}$$

where $\mathbf{Z}_{it}$ is a row of the matrix of exogenous variables, $\mathbf{X}^*$, and υ is a vector of parameters (to be estimated) that when combined with $\mathbf{Z}$, yield the diagonal, σ, of the covariance matrix of $\varepsilon\mathbf{^*}$.

This completes the description of the model. It is straightforward to write a likelihood function for Eqn. (13), using the whitened data in Eqn (18) and correcting for heteroskedasticity using Eqn. (19). The parameter vector that maximizes this likelihood function is desired. Parameters would include the coefficients of $\mathbf{X^*}$ as well as the elements of υ (heteroskedasticity) and the spatial and temporal autocorrelation terms, δ and ρ.

C. The Data.

The data set we use is annual county observations for the US, 1977-95. Because we need lagged values, we can use 18 years of data for over 3000 counties -- over 50,000 observations, of which approximately 41,000 involve positive corn output. We use data on climate, weather, soil characteristics, economic variables, corn output and acres planted to corn. Climate variables are computed from county-level weather data from 1930 through the year prior to the year in question. Thus the climate variables for a single county change modestly over our sample. All other data used, however, are from the 1977-95 period. Weather for a county is constructed from weather station information, following approximately the method of Mendelsohn et al (1994). Weather is normalized by subtracting the mean of a particular weather variable from the realization of that variables and dividing the difference by the standard error of the variable. The weather data that we use are April and July average temperature and total rainfall for the month (four variables). For climate, we use the means and standard errors of April and July temperature and precipitation as well as the covariance between July temperature and precipitation.

Soil characteristics were assumed to be unvarying over the sample period. Thus we used information from the 1982 National Resource Inventory for every year in the sample. Price data is from two sources. For expected grain prices, we used the average daily closing price (weighted by trading volume) for futures contracts traded in April and having delivery in July.[12] For input prices, we used a USDA index of the variable cost of producing one bushel of corn in a given year. All price data was deflated by the urban CPI. Census data was used for county characteristics (income,

[12] The July delivery date avoids potential distortions from thin markets or from the influence of contracts which are near their expiration date.

population, per captia income and population density). These data are interpolated from the decennial census data.

Table I summarizes the variables used and their statistical properties.

D. Estimation and Results

The problem is to estimate eqn. (9-10), correcting for statistical problems discussed above. We adopt a mixed logarithmic functional form in estimating these equations. Specifically, logarithms of economic variables (prices and quantities) are used whereas soil characteristics, dummy variables and weather/climate are used in their natural form. To allow for non-linearities in the functional form, we include squared terms for weather, geographic, and census variables, but we do not proceed with a full second order expansion because of the large number of variables. There are three equations to estimate, the probit sample selection equation, the acreage equation (Eqn. 9) and the output equation (Eqn. 10). The exogenous variables for the acreage equation and the probit are identical (except for the sample selection term). We consider April and July measures of climate (precipitation, temperature, standard errors of these and the covariance of July precipitation and temperature) and the squares of these measures. We also consider the CCC loan rate as a proxy for the price of capital, the price of corn, soybeans and wheat, an input price index, soil characteristics, county urbanization variables, and a time trend. For the output equation, we consider these same variables except for the price of substitute crops, which we omit, weather realizations (April and July precipitation and temperature), which we include, and acreage planted, which we also include. These variables are defined more precisely in Table I.

Tables II and III show the results of the estimation of eqn. (9-10). Temporal autocorrelation is assumed to be AR1 whereas spatial autocorrelation is proportional to the inverse of the square of the distance between counties, taking into account counties within 500 miles. In adjusting for heteroskedasticity, error variances are assumed proportional to a linear combination of a constant, county size (siz) and the July temperature-preciptitation covariance (jcv). Maximum likelihood is used to estimate these equations. Our preferred model for both equations is the one with the corrections for autocorrelation and heteroskedasticity.

Note that the statistical corrections have a significant effect. The temporal and spatial autocorrelation parameters (act and acs) are highly significant. Heteroskedasticity is significant in the acreage equation (sig, sigc and sigs are the elements of υ in Eqn. 19; sig is the constant, sigc is the coefficient on jcv and sigs is the coefficient on siz) but the parameters are not individually significant in the output equation (Table III). This is no doubt because the output equation exhibits constant returns to scale; the coefficient on acreage (yac) is essentially unity. Thus the output equation is essentially a yield equation. It is not surprising that variables such as the size of the county have no effect on the variance of yield.

Examining the acreage equation in more detail (Table II), note the most of the variables have the intuitively correct sign. When a variable and its square are both in the regression, we would generally expect the squared term to have a negative coefficient, indicating that the plot of the dependent variable as a function of the independent variable is concave downward, reaching a maximum for some value of the variable. With a few exceptions, this is in fact the case. With regard to prices, higher prices of corn increase acreage planted (pcc) and higher prices for substititues decrease acreage planted (pso, pwh). Unfortunately, all of the price effects are insignificant or barely significant.

Figure 2 shows how acreage planted responds to climate. Shown in the figure is acreage in the median county as a function of mean July precipitation, which takes the value 3.7" for the median county. There is obviously some average July precipitation for which the maximum acreage is planted to corn,[13] and that is above the precipitation for the median county. Of course there is no need for the median county to be at that maximum, and it is not. A similar picture is painted in Figure 2, except for the case of mean July temperature, which takes the value 76.1°F for the median county. The median county's July temperature is very close to that which yields a maximum.

Focusing now on the output equation (Table III), somewhat surprisingly, the number of significant variables is not great. Acreage planted to corn is significant and essentially unity, indicating constant returns to scale. Weather is highly significant. Higher than normal April precipitation (zap) and July temperatures (zjt) decrease yield whereas higher than normal April temperature (zat) and July precipitation (zjp) increase yield. This is totally consistent with intuition and in fact with the literature (compare the results for July with Thompson, 1986). How do we interpret the coefficient values on these z-scores? The coefficient on April precipitation is -0.0126. This means that a unit increase in the z-score reduces yield by 1.3%. A unit increase in the z-score is equivalent to a one standard deviation increase in April precipitation. From Table I, we see that one standard deviation in April precipitation is approximately 1.5 inches. Thus April precipitation that is one inch greater than expected reduces yield by slightly less than 1%. Using this approximation, yield seems to be most sensitive to July mean temperature.

Other significant coefficients in the output equation include the prices of corn and inputs as well as time. For some reason, higher prices of corn decrease output (pco). The only explanation for this is that higher prices induce increased planting in more marginal locations. One other

[13] When y depends on $ax^2 + bx$ as well as other variables not involving x, clearly y attains a maximum or minimum with respect to x when $x = -b/2a$.

significant variable is the time trend, indicating an annual increase in yield of about 1.4%, presumably due to technical change.

It is appropriate to note in Table III that before making statistical corrections for autocorrelation and heteroskedasticity, nearly all of the coefficients were significant. Only after the statistical corrections were made did significance drop. Most of the other econometric analyses of corn yield (referenced earlier in this paper) do not correct for autocorrelation. Our results suggest that this is an important factor.

V THE SUPPLY EFFECTS OF ADJUSTMENT

We now turn to the question of the adjustment that may occur due to an unanticipated and unobserved change in the climate. Our approach will be to posit a change in the climate, a change that the farmer does not directly observe. The climate change will generate different weather and over time the farmer will become aware of the new climate. Using our estimate of corn supply for a "typical" farm/county, we would ideally like to simulate both the learning process and the output changes that occur while learning is taking place.

To simplify our climate change scenario, we adopt the same definition of climate change as used by Mendelsohn et al (1994). Their climate change scenario is a 5^{o}F increase in temperature and an 8% increase in precipitation (April and July). We assume the variance of each variable does not change and we ignore covariance between variables, except for July temperature-precipitation. Note in particular the mean July rainfall (3.6") and temperature (75.7^{o}F). The variance of these estimates of the mean will be the sample variances divided by the number of observations (approximately 50). We assume temperature and rainfall are drawn from a normal distribution with mean and variance as in Table I (ignoring the covariance for ease of computation). Figure 4 shows how a Bayesian farmer would respond to an instantaneous increase in July temperature of 5 degrees. Note the slow rate of learning, primarily because new observations only slowly dominate the historic record.

However, for our simulations, we assume this climate change occurs gradually, in fact linearly over a century. Using a multivariate version of eqn. (7), Figure 5 shows how the prior on mean July temperature is expected to evolve over time under this climate change scenario (broken line), while the actual mean July temperature follows the solid line. Since learning takes place in response to realized temperatures, learning will be slightly different for different draws from the distribution of weather. Figure 5 shows learning averaged over 1000 realizations of the weather. Note that learning is relatively rapid at first although it takes some time for the farmer to completely realize the true new mean of temperature.

The second step is to combine the mulitvariate version of eqn. (7) with eqn (9-10), to determine how expected acreage and output will evolve over time. This is a complex relationship that we compute numerically. We start by generating a particular trajectory of future weather, using our prior on the distribution of weather. Using that particular trajectory of future weather, we compute the farmer's subjective estimate of the climate over time (using the multivariate version of eqn. 7), and the estimated acreage and output function, eqn. (9-10). We can estimate these as a function of time as the farmer is learning about the climate and compare this to the output and acreage that would prevail if the farmer were fully informed of the climate. This generates a trajectory over time that approaches the "full information" output and acreage. We repeat this process for randomly drawn future weather trajectories and average the resulting trajectories.

Figure 6 shows how corn acreage responds in this situation. We focus our attention on the median farmer/county; in other words, we examine an artificial county with the median of each of the exogenous variables as given in Table I. The solid line is the corn acreage for the median county under perfect information about the changing climate. The broken line shows the acreage planted under incomplete information about the climate shock. In this case, for the median county, it is optimal to decrease acreage in response to higher temperatures. Apparently, corn does not grow as well at these higher temperatures and precipitation so the optimal response is to switch to another crop (not represented in our model). The broken line shows the path of the poorly informed farmer as he slowly reduces acreage planted.

A similar analysis can be done with corn output conditional on acreage planted. Figure 7 shows how corn output changes under these two information conditions. The solid line shows the evolution of corn output under perfect information about the climate change. The broken line shows how output evolves for the imperfectly informed farmer. We know from the output equation that yield is fairly constant. Most of this decline in output is due to a decline in acres planted to corn.

At first blush, these results suggest that it is good to be ill-informed. After all, in Figure 7, there is more corn output under imperfect information than under perfect information. This is not the correct interpretation however. The farmer should be responding to the changed climate by taking acreage out of corn and putting it in wheat (for example). This gives the highest level of profit. The ill-informed farmer is not taking enough acreage out of corn.

The loss in corn output due to the climate change is represented in Figure 7 by the drop in output from approximately 5.4 million bushels to less than 1 million bushels. This is a substantial drop. However, the what happens to the median county in no way indicates what might happen to the rest of the country. Furthermore, the significance of this drop can only be determined by examining what happens to other crops as corn output drops. Despite this, if we let the area between the dashed line and the solid line in Figure 7 be the adjustment costs in output terms, we see that it is a significant compared to the adaptation loss in output.

V. CONCLUSIONS

In this paper we have presented a method for estimating the adjustment costs associated with an unanticipated and unobserved change in the climate. The important result of this paper is a theoretical framework for quantifying the adjustment costs. We show that these interim adjustment costs may be significant, even if farmers can completely adjust, without loss, to climate change. Future work could involve refining the empirical estimation to move away from a single crop, possibly examing overall farm output. Other improvements might involve examining other models of learning, other that simple Bayesian learning.

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Data Appendix

The weather data used for estimation are weighted averages of all weather stations within 500 miles (weighted by the inverse of the distance). The meteorological station data is from the U.S. Historical Climatology Network Serial Temperature and Precipitation Data (NOAA, 1996), available electronically at ftp.ncdc.noaa.gov/pub/data/ushcn. Geographic information for each county comes from two sources. Climate data is constructed as an average of the last 30 years for each county.

The county centroid longitude and latitude are from the National Weather Service Shapefile Catalog (NOAA, 1997), drawn form USGS data (USGS 1:2,000,000 DLG), available electronically at ftp.nws.noaa.gov/modernize/shapemap/county. The elevation data comes for the National Resource Inventory soils database, as supplied by ZIPFIP from the USDA Economic Research Service (1982), available electronically at ftp.mannlib.cornell.edu/data-sets/general/93015. The conversion factor used for distance (both to generate weather estimates and for the autocorrelation correction) was 90 miles per degree, which is approximately correct in the center of the United States.

The soil variables are county-wide estimates that were generated from the 1982 National Resource Inventory, and are also supplied by ZIPFIP from the USDA Economic Research Service (USDA-ERS, 1982).

The price data comes from two sources. For expected grain prices, we used the average daily closing price (weighted by trading volume) for futures contracts traded in April and having delivery in July, as supplied by Tick Data, Inc. (1996). For input prices, we used an index supplied by the Department of Agriculture (USDA-ERS, 1996), available electronically at ftp.mannlib.cornell.edu/data-sets/inputs/94010, which approximates the variable cost associated with producing one bushel of corn in a given year. Finally, all of the prices for grains and inputs are adjusted by the consumer price index, seasonally adjusted U.S. cities average for urban consumers, base 1982-1984, from the U.S. Bureau of Labor Statistics (1997).

The census data is from interpolated values, using decennial census data and interim surveys, constructed at the county level by the U.S. Census Bureau, and supplied by the U.S. Department of Commerce (1997).

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Table 1: Summary of variables, 41,126 Observations

NB: Statistics over counties with positive corn production

Data	Mean	Median	Std. Dev.	Min	Max	Description
aps	1.501	1.424	0.501	0.252	4.983	April precipitation standard deviation (inches)
aps2	2.504	2.027	1.801	0.064	24.826	aps * aps
apx	3.301	3.345	1.071	0.188	5.694	April precipitation mean (inches)
apx2	12.045	11.188	6.827	0.035	32.418	apx * apx
ats	2.86	2.777	0.542	1.729	6.082	April temperature standard deviation (degrees F ÷ 10)
ats2	8.475	7.714	3.245	2.989	36.99	ats * ats
atx	5.351	5.384	0.756	3.655	7.415	April temperature mean (degrees F ÷ 10)
atx2	29.209	28.991	8.206	13.356	54.982	atx * atx
gel	10.625	8.13	10.36	-1.0	75.74	elevation (feet ÷ 100)
gel2	220.23	66.097	534.095	0.0	5,736.54	gel * gel
gln	-8.99	-9.018	0.921	-12.382	-7.236	longitude (degrees ÷ 10)
gln2	81.659	81.333	17.306	52.358	153.314	gln * gln
glt	3.852	3.833	0.443	2.62	4.884	latitude (degrees ÷ 10)
glt2	15.032	14.692	3.404	6.862	23.856	glt * glt
jcv	-1.264	-1.137	1.047	-13.481	3.542	July covariance of precipitation and temperature
jcv2	2.693	1.293	4.947	0.0	181.741	jcv * jcv
jps	1.551	1.555	0.457	0.031	5.908	July precipitation standard deviation (inches)
jps2	2.616	2.417	1.603	0.001	34.906	jps * jps
jpx	3.828	3.79	1.311	0.014	8.888	Ju;y precipitation mean (inches)
jpx2	16.376	14.367	10.372	0.0	78.99	jpx * jpx
jts	2.105	1.974	0.575	0.863	9.706	July temperature standard deviation (degrees F ÷ 10)
jts2	4.759	3.896	3.114	0.744	94.204	jts * jts
jtx	7.575	7.611	0.439	6.07	9.797	July temperature mean (degrees F ÷ 10)
jtx2	57.58	57.924	6.658	36.841	95.988	jtx * jtx
lmb	0.288	0.362	0.308	0.0	3.825	lambda -- sample selection correction factor
pcc	0.7	0.637	0.17	0.451	0.975	CCC loan rate (ln of percentage rate)
pco	5.496	5.123	0.335	5.027	6.034	futures price of corn (ln ¢/bushel)
pin	5.528	5.392	0.165	5.296	5.821	price of variable inputs, USDA (ln, ¢/bushel)
pso	6.396	5.956	0.319	5.956	6.993	futures price of wheat (ln, ¢/bushel)
pwh	5.749	5.442	0.305	5.367	6.217	futures price of soybeans (ln, ¢/bushel)
scl	0.113	0.0	0.317	0.0	1.0	1 if clay, 0 otherwise
sfl	0.165	0.086	0.206	0.0	1.0	Fraction of acres in county prone to flooding
sir	0.102	0.0	0.231	0.0	1.0	Fraction of acres in county irrigated
siz	6.411	6.418	0.628	4.431	9.907	Size of county (ln square miles)
skf	0.271	0.283	0.088	0.0	0.469	k-factor (soil erodability index)
ssa	0.012	0.0	0.044	0.0	0.522	Fraction of acres in county treated for high salinity
ssl	1.841	1.615	1.3	0.0	13.526	Slope (average distance in feet to water basin)
ssn	0.124	0.0	0.33	0.0	1.0	1 if sandy, 0 otherwise
swt	0.061	0.012	0.101	0.0	0.949	Fraction of acres in county that are wetlands
tim	10.296	19.0	5.187	2.0	19.0	Time index (1978=2)
xin	1.254	1.285	0.138	0.727	1.875	County total income per capita(ln 10,000$)
xin2	1.591	1.65	0.354	0.528	3.515	xin * xin
xpo	1.013	1.004	0.12	0.605	1.549	County total population (ln 1,000s persons)
xpo2	1.04	1.008	0.251	0.366	2.4	xpo * xpo
yac	8.902	7.696	1.963	2.303	12.863	acreage (ln acres)
you	8.738	7.659	2.16	1.253	13.295	output (ln 1,000s of bushels)
zap	0.023	0.078	1.122	-4.359	6.201	actual April precipitation z-score
zat	0.009	-0.408	1.044	-3.256	3.541	actual April temperature z-score
zjp	0.157	-0.225	1.177	-14.453	8.935	actual July precipitation z-score
zjt	0.06	0.267	1.006	-5.023	3.561	actual July temperature z-score

Other parameters

act	temporal autocorrelation parameter
acs	spatial autocorrelation parameter
sig	effect of constant on variance of residual (heteroskedasticity)
sigc	effect of jcv on variance of residual (heteroskedasticity)
sigs	effect of siz on variance of residual (heteroskedasticity)

NB: Median is calculated for 1995 only.

Table II: Estimates for Acreage Equation (Dependent variable: yac)

	No autocorrelation or hetero correction:			With autocorrelation & heteroskedasticity:		
	estimate	std. err.	t-stat	estimate	std. err.	t-stat
act	n.a.	n.a.	n.a.	0.6675	<.0001	>1000 **
acs	n.a.	n.a.	n.a.	0.0003	<.0001	>1000 **
sig	1.3547	0.0159	85.2013 **	-0.3199	0.0153	-20.9766 **
sigc	n.a.	n.a.	n.a.	-0.0296	0.002	-14.8028 **
sigs	n.a.	n.a.	n.a.	0.1575	0.0028	55.3967 **
con	-301.4335	4.6933	-64.2269 **	-391.6426	1.0934	-358.1973 **
aps	1.0552	0.1404	7.5132 **	0.2565	<.0001	>1000 **
aps2	-0.104	0.0343	-3.0281 **	0.1366	0.0172	7.937 **
apx	0.9708	0.0758	12.809 **	0.1725	0.0222	7.7666 **
apx2	-0.3637	0.0094	-38.6751 **	-0.2367	0.0084	-28.0554 **
ats	7.796	0.2005	38.8921 **	3.61	0.2382	15.1576 **
ats2	-1.1657	0.0318	-36.6247 **	-0.4884	0.0368	-13.2811 **
atx	-4.858	0.4788	-10.1467 **	-9.3393	0.4829	-19.3384 **
atx2	0.371	0.0457	8.1101 **	0.9222	0.0429	21.5194 **
gel	-1.4802	0.0297	-49.9112 **	-1.4478	0.0346	-41.8658 **
gel2	0.0508	0.0055	9.3043 **	0.0238	0.0056	4.2596 **
gln	-11.3158	0.3251	-34.8083 **	-16.5001	<.0001	>1000 **
gln2	-0.5568	0.0174	-31.9077 **	-0.8282	<.0001	>1000 **
glt	25.2303	1.2075	20.8944 **	46.9548	0.6768	69.3773 **
glt2	-3.0577	0.1474	-20.7509 **	-5.7162	0.0926	-61.73 **
jcv	-0.8246	0.0262	-31.4173 **	-0.7212	0.0261	-27.6669 **
jcv2	-0.1831	0.004	-46.0892 **	-0.1479	0.0034	-43.2295 **
jps	-4.187	0.1234	-33.9299 **	-1.5962	0.0878	-18.1833 **
jps2	0.8686	0.0313	27.7773 **	0.2001	0.0233	8.5834 **
jpx	2.3527	0.061	38.5977 **	1.5072	0.0614	24.5634 **
jpx2	-0.1718	0.0058	-29.8807 **	-0.1122	0.0061	-18.4465 **
jts	-2.5361	0.1008	-25.1625 **	-3.1134	0.0726	-42.8634 **
jts2	0.2876	0.0139	20.6568 **	0.376	0.0104	36.0724 **
jtx	48.1955	0.7849	61.4019 **	57.1976	0.7129	80.2298 **
jtx2	-3.0857	0.0514	-60.0133 **	-3.7897	0.0442	-85.8077 **
lmbd	2.1662	0.0675	32.0747 **	0.9792	0.0243	40.3503 **
pcc	0.1564	0.0671	2.3296 *	0.233	0.1477	1.5771
pco	0.1084	0.0806	1.3458	0.1578	0.1789	0.8823
pin	1.0186	0.1861	5.4734 **	1.5095	0.4148	3.6388 **
pso	-0.2245	0.0831	-2.7026 **	-0.0699	0.1841	-0.3798
pwh	-0.3183	0.0934	-3.4091 **	-0.3426	0.2067	-1.658
scl	-0.2059	0.0231	-8.9172 **	-0.2439	0.0165	-14.7899 **
sfl	-0.7842	0.0356	-22.0103 **	-0.754	0.0267	-28.2229 **
sir	0.0862	0.033	2.6136 **	0.0406	0.0252	1.6138
siz	0.5976	0.0204	29.2851 **	0.9739	0.0133	73.3084 **
skf	0.9383	0.1226	7.6514 **	1.268	0.0912	13.9085 **
ssa	-0.5768	0.163	-3.5385 **	-0.0304	0.1212	-0.2506
ssl	-0.0161	0.0058	-2.7611 **	-0.0051	0.0044	-1.1578
ssn	0.1976	0.0311	6.3501 **	0.2885	0.0231	12.4666 **
swt	0.2795	0.0767	3.6428 **	-0.1206	0.0574	-2.1007 *
tim	-0.058	0.0042	-13.7935 **	-0.0197	0.0101	-1.9516
xin	-35.3055	0.8279	-42.6441 **	5.6843	0.1643	34.6043 **
xin2	16.5037	0.3752	43.9905 **	-0.8952	0.0065	-137.6565 **
xpo	67.7243	1.0114	66.9581 **	24.4568	0.1835	133.2734 **
xpo2	-35.2697	0.5442	-64.8157 **	-12.8171	0.009	>1000 **

*significant at 5% confidence level **significant at 1% confidence level

Table III: Estimates for Output Equation (dependent variable = you)

	No autocorrelation or hetero correction:			With autocorrelation & heteroskedasticity:		
	estimate	std. err.	t-stat	estimate	std. err.	t-stat
Act	n.a.	n.a.	n.a.	0.1959	<.0001	>1000 **
Acs	n.a.	n.a.	n.a.	1.2633	0.0002	>1000 **
Sig	0.2825	0.0258	10.9534 **	-0.029	0.296	-0.0981
Sigc	n.a.	n.a.	n.a.	-0.0174	0.0201	-0.8654
Sigs	n.a.	n.a.	n.a.	0.0302	0.0428	0.7056
Constant	-0.0171	0.1535	-0.1114	-8.4512	3.9275	-2.1518 *
Yac	1.071	0.001	1071 **	0.9989	0.0005	>1000 **
Aps	-0.1881	0.0284	-6.62 **	-0.1808	0.2408	-0.7508
aps2	0.0492	0.007	7.0339 **	0.0464	0.0591	0.7863
Apx	-0.201	0.0148	-13.6063 **	0.2274	0.1418	1.6045
apx2	0.0164	0.0019	8.4357 **	-0.0337	0.0181	-1.8627
Ats	1.4734	0.042	35.0719 **	0.8573	0.3604	2.3788 *
ats2	-0.2194	0.0066	-33.0109 **	-0.1189	0.0577	-2.0609 *
Atx	1.4365	0.0871	16.4964 **	0.2302	0.8272	0.2783
atx2	-0.1333	0.0078	-17.0501 **	-0.0207	0.0844	-0.2448
Gel	0.0241	0.0063	3.801 **	-0.0338	0.0583	-0.5798
gel2	-0.0172	0.001	-16.6499 **	0.0017	0.0105	0.1636
Gln	-0.3362	0.0491	-6.8418 **	-1.0219	0.5771	-1.7708
gln2	-0.0125	0.0027	-4.6357 **	-0.0541	0.0316	-1.7106
Glt	3.0076	0.145	20.7435 **	2.1635	2.2367	0.9673
glt2	-0.4131	0.0186	-22.1631 **	-0.2749	0.2657	-1.0345
Jcv	0.0008	0.0055	0.1532	-0.0363	0.0492	-0.7388
jcv2	-0.002	0.0008	-2.4288 *	0.0008	0.007	0.12
Jps	0.1282	0.0254	5.0541 **	0.2052	0.2275	0.9022
jps2	-0.0119	0.0065	-1.8461	-0.0362	0.057	-0.6344
Jpx	-0.0171	0.0124	-1.3824	-0.1169	0.1096	-1.066
jpx2	0.0061	0.0012	5.2346 **	0.0046	0.0109	0.4241
Jts	-0.3983	0.0181	-21.9635 **	-0.3711	0.2072	-1.7912
jts2	0.0419	0.0026	16.3222 **	0.0371	0.0304	1.2211
Jtx	-3.4477	0.1029	-33.5167 **	-0.7718	0.4642	-1.6625
jtx2	0.2121	0.0061	34.6951 **	0.0468	0.027	1.7318
Lmbd	0.0709	0.0094	7.5084 **	-0.051	0.0406	-1.2585
Pco	-0.066	0.0138	-4.789 **	-0.1237	0.0383	-3.227 **
Pin	0.2079	0.0329	6.3252 **	0.3018	0.1014	2.977 **
Scl	-0.0172	0.0047	-3.6597 **	-0.0002	0.0627	-0.003
Sfl	0.018	0.0074	2.4238 *	0.0122	0.0946	0.1295
Sir	0.0674	0.0068	9.8711 **	-0.0033	0.0857	-0.0387
Siz	-0.0463	0.0036	-12.8009 **	-0.0198	0.0415	-0.4763
Skf	-0.0019	0.0255	-0.0757	-0.0697	0.3287	-0.2119
Ssa	-0.079	0.034	-2.3247 *	-0.035	0.4449	-0.0787
Ssl	0.0009	0.0012	0.7514	-0.0006	0.0156	-0.0398
Ssn	0.0056	0.0064	0.866	-0.0257	0.0827	-0.3108
Swt	-0.0686	0.0159	-4.3171 **	-0.0011	0.2033	-0.0056
Tim	0.0155	0.0007	21.8774 **	0.0137	0.0036	3.7764 **
Zap	-0.0127	0.0013	-9.5558 **	-0.0126	0.0031	-4.0971 **
Zat	0.035	0.0014	24.9005 **	0.0092	0.0035	2.6006 **
Zjp	0.0345	0.0014	24.6818 **	0.0187	0.0033	5.5933 **
Zjt	-0.0659	0.0017	-38.6828 **	-0.0387	0.0036	-10.9033 **

*significant at 5% confidence level **significant at 1% confidence level

Figure 1: Value of land as a function of climate or weather
Source: Adapted from Mendelsohn et al, 1994.

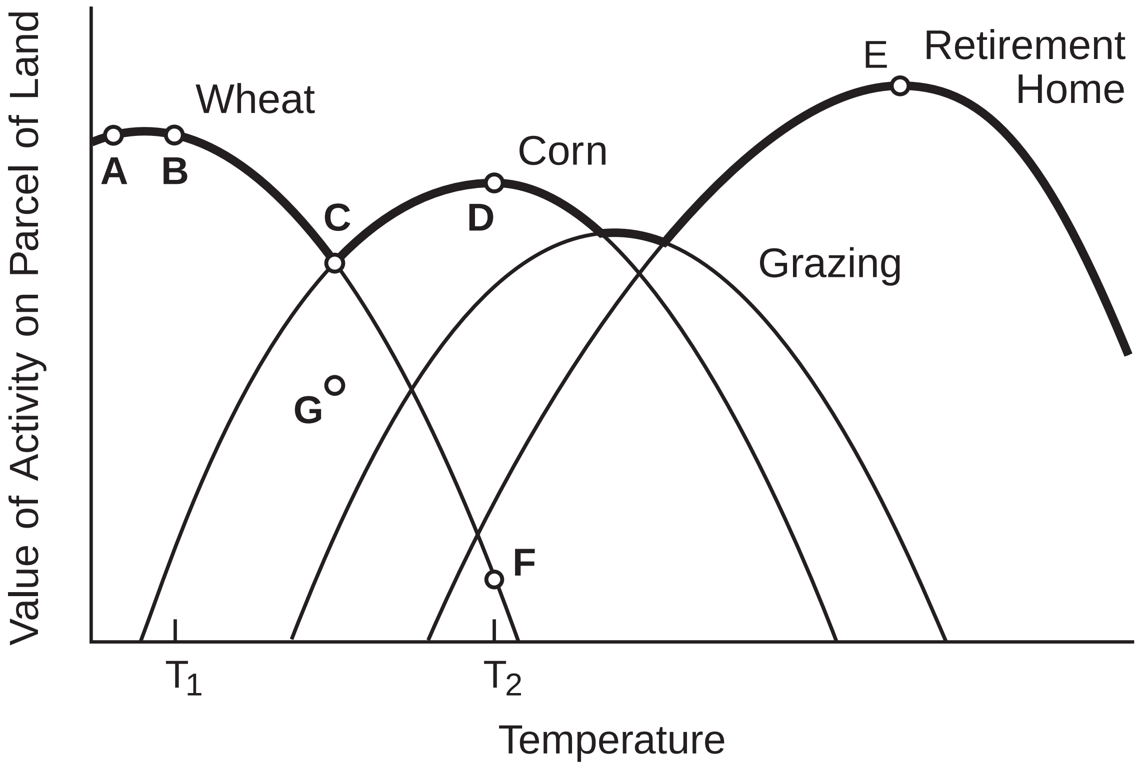

Figure 2: Acreage Planted as a Function of July Precipitation for Median County

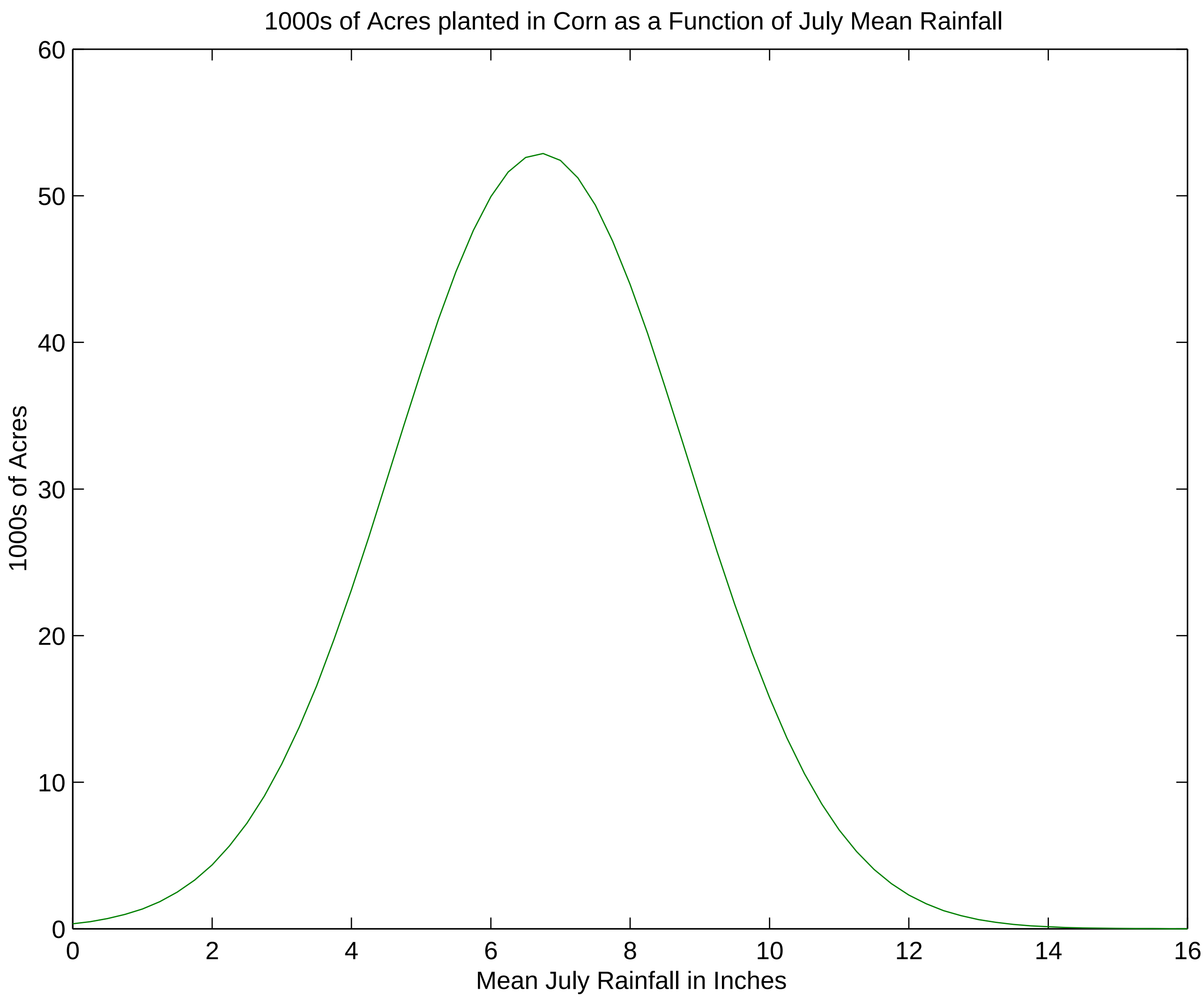

Figure 3: Acreage Planted as a Function of July Temperature For Median County

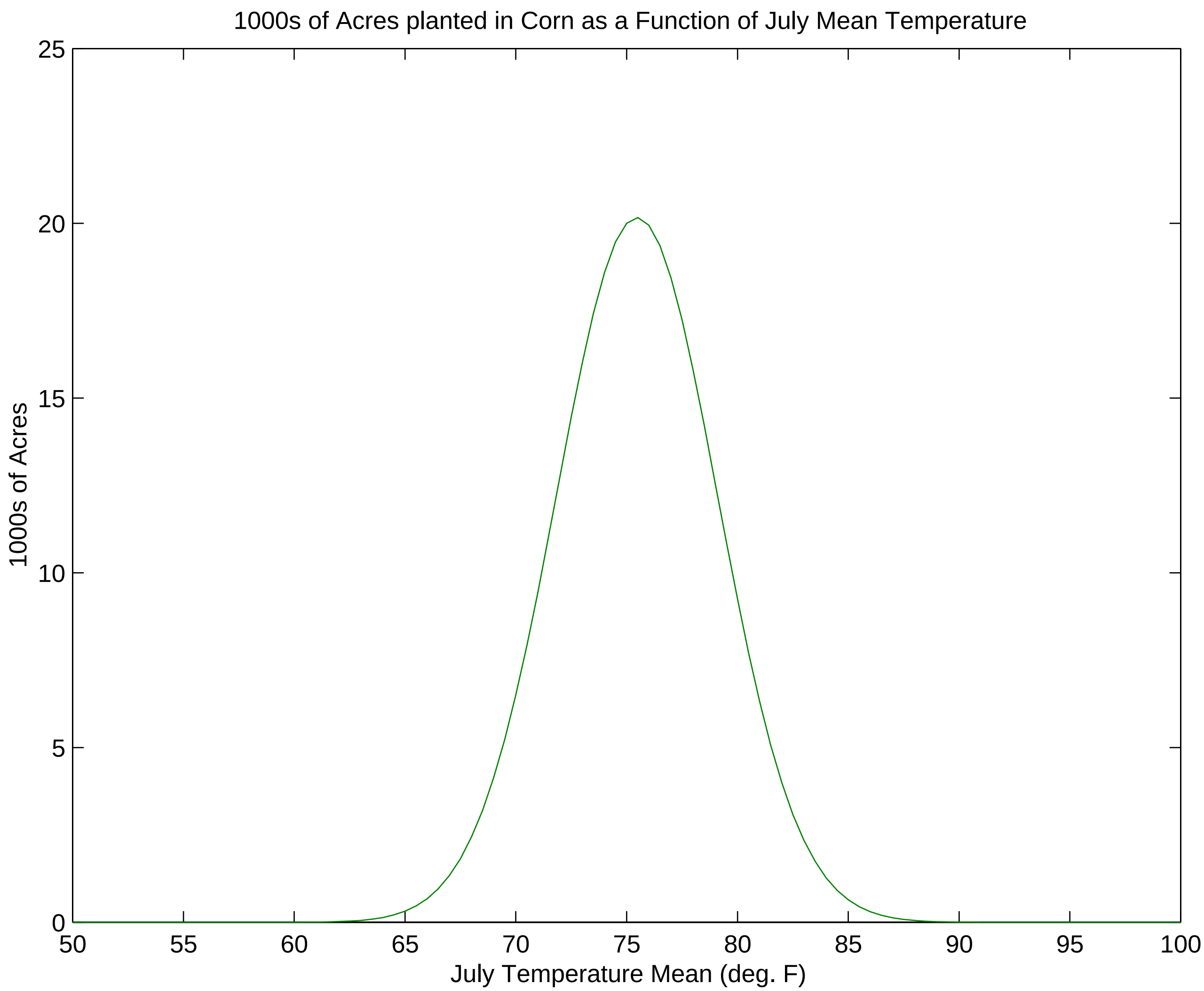

Figure 4: Learning about an unobserved 5°F increase in temperature.
Prior: 75.9°F, standard error 0.078°F.

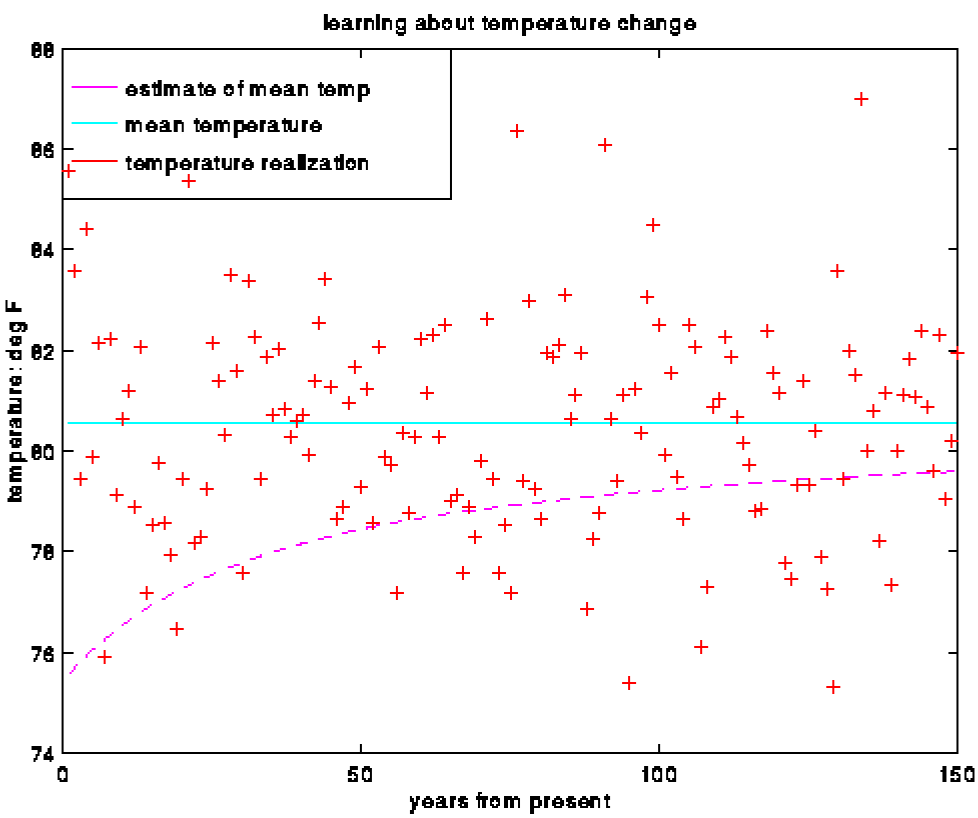

Figure 5: Actual and Estimated Mean July Temperature, under assumed climate change

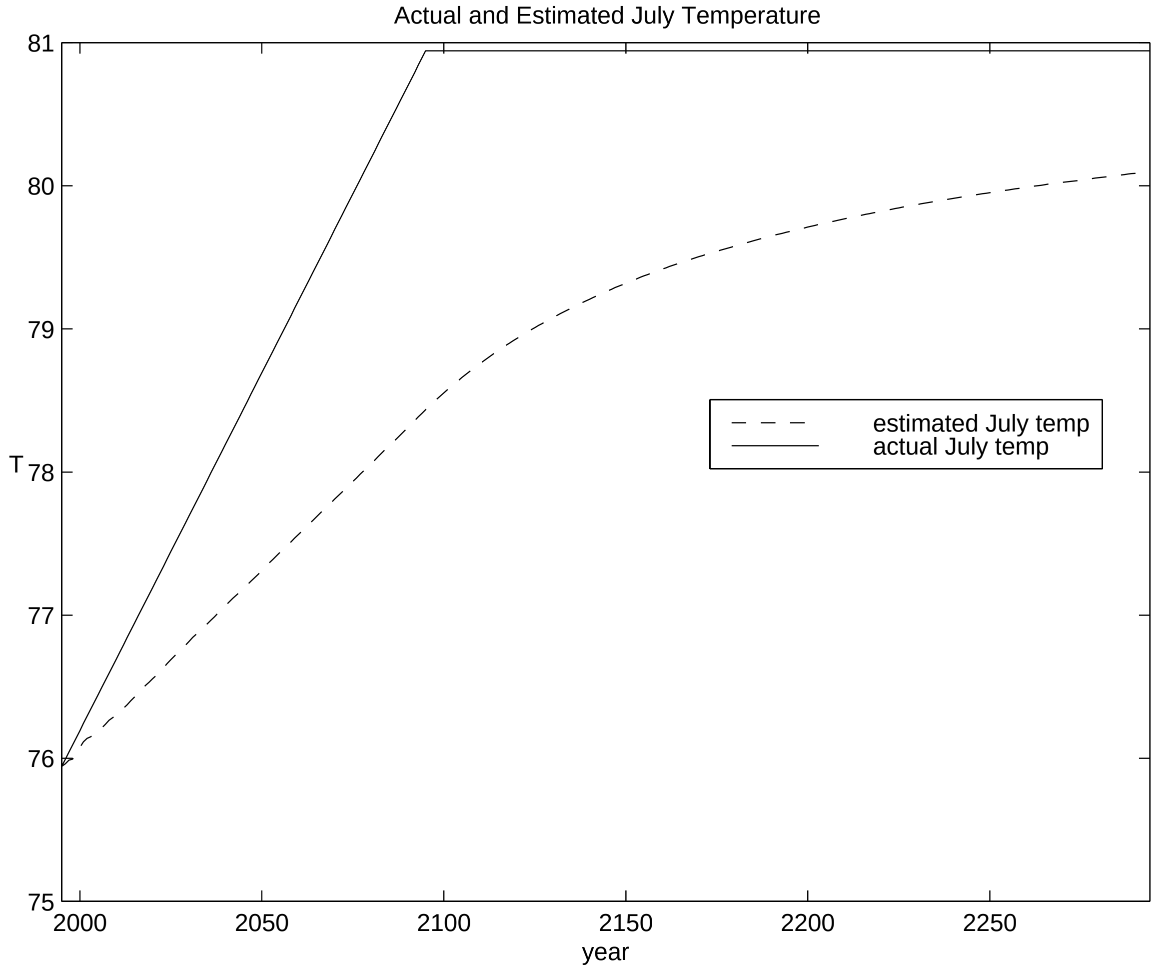

Figure 6: Acres planted to corn in median county, under assumed climate change

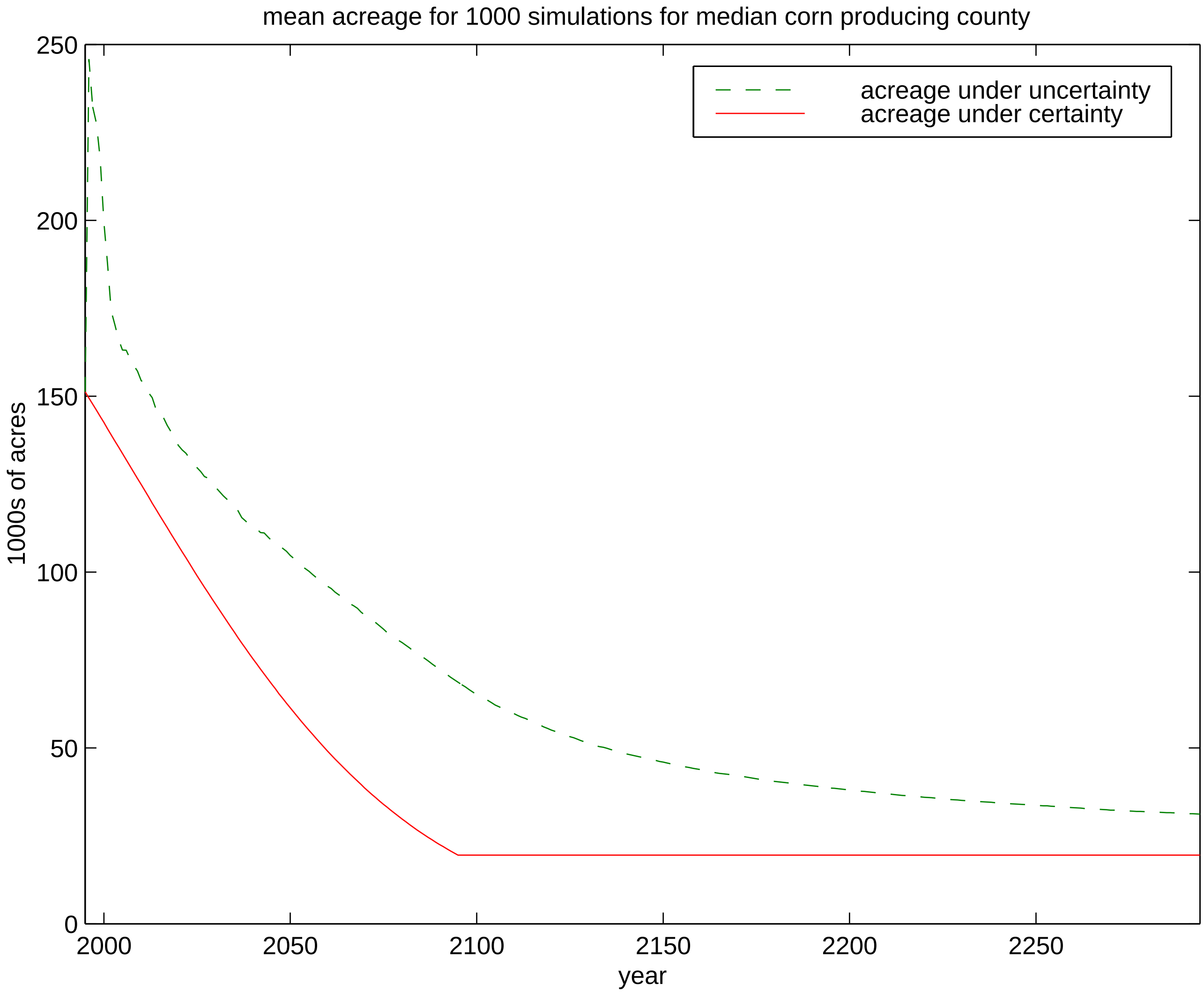

Figure 7: Ln corn output for median corn producing county under assumed climate change