IMPROVING THE REALISM OF MODELING AGRONOMIC ADAPTATION TO CLIMATE CHANGE: SIMULATING TECHNOLOGICAL SUBSTITUTION

WILLIAM E. EASTERLING [1], NETRA CHHETRI [1] and XIANZENG NIU [2]

[1] *Department of Geography, The Pennsylvania State University, University Park, PA 16802, U.S.A.*
E-mail: easter@gis.psu.edu

[2] *Department of Crop and Soils Science, The Pennsylvania State University, University Park, PA 16802, U.S.A.*

Abstract. The purpose of the paper is to propose and test a new approach to simulating farmers' agronomic adaptation to climate change based on the pattern of adoption of technological innovation/substitution over time widely described as a S-shaped (or logistic) curve, i.e., slow growth at the beginning followed by accelerating and then decelerating growth, ultimately leading to saturation. The approach we developed is tested using the Erosion Productivity Impact Calculator crop model applied to corn production systems in the southeastern U.S. using a high-resolution climate change scenario. Corn is the most extensively grown crop in the southeastern U.S. The RegCM limited area model nested within the CSIRO general circulation model generated the scenario. We compare corn yield outcomes using this new form of adaptation (logistic) with climatically optimized (clairvoyant) adaptation. The results show logistic adaptation to be less effective than clairvoyant adaptation in ameliorating climate change impacts on yields, although the differences between the two sets of yields are statistically significant in one case only. These results are limited by the reliance on a single scenario of climate change. We conclude that the logistic technique should be tested widely across climate change scenarios, crop species, and geographic areas before a full evaluation of its effect on outcomes is possible.

1. Introduction

In this research, we investigate how the procedure used by modelers to simulate adaptation to the impacts of climate change influences outcomes. The purpose of the paper is to propose and test a new approach to simulating farmers' agronomic adaptation to climate change based on a well-known model of the adoption of technological innovation and technological substitution. Although economics and other social factors influencing adaptation are not considered, we assert that the approach is a robust test of the effect that the timing of adaptation, relative to the pace of climate change, has on outcomes. The approach is guided by the considerable literature on varying rates at which individual decision makers in a population adopt new innovations or make technological substitutions (discussed by Ruttan, 1996). According to that literature not all farmers are likely to adopt changes in their operations in response to climate change at the same time. Some will adopt at the earliest indications of climate change, a great many will wait to see what others

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are doing before adopting, and a few will lag behind the majority. The shape of the distribution implied in the last statement takes on the classic S-shaped or logistic form. The approach we developed is tested using the Erosion Productivity Impact Calculator crop model applied to corn production systems in the southeastern U.S. using a high-resolution climate change scenario. The RegCM limited area climate model nested within the CSIRO general circulation model generated the scenario.

Climate change impact science is constrained by assumptions about the future, principally, the distinguishing features of climate change, how changing technological, economic and policy regimes may mediate impacts, and how decision makers may deal with future climate risk. The indiscriminate application of those assumptions has been problematic; it complicates comparisons of results between studies and introduces unacceptably large uncertainty for policy formulation. We believe that assumptions of how ecosystems and society will attempt to adapt to climate change are among the strongest influences on final outcomes of climate change. Some studies have shown that those assumptions potentially convert negative outcomes into positive ones or vice versa (Mearns et al., 2001). Yet, the importance of including adaptation in the calculus of the consequences of climate change has been demonstrated conclusively in climate impact studies spanning more than a decade of research in agriculture (Rosenberg, 1982; Parry and Carter, 1988; CAST, 1992; Easterling et al., 1993; Rosenzweig and Parry, 1994; Smit et al., 1996; Gitay et al., 2001), sea level rise (Yohe and Schlesinger, 1998) water resources (Frederick and Schwarz, 1999) and other sectors. By adaptation we refer to the deliberate actions of humans and the reorganization of natural ecosystems to cope with challenges and opportunities afforded by climate change. The remainder of this paper will present background information on technological diffusion, sketch out the methodology of this research, describe results of an application of the methodology to cropping systems in the southeastern U.S., and discuss the major findings and conclusions in light of their methodological and policy implications.

2. Background

The exact method by which adaptations are implemented in climate impact models varies widely. In studies using crop process models, the focus of this research, adaptation is simulated by adjustments to climate sensitive variables in order to represent the obvious agronomic countermeasures of farmers to combat negative impacts of climate changes or to take advantage of positive ones. Such countermeasures include, for example, changes in planting and harvesting dates, in cultivar traits usually to alter the length of time needed by the crop to reach physiological maturity, in fertilizer application amounts, in irrigation timing and amounts, and, in the extreme, in crop species.

Countermeasures typically are applied by adjusting parameter values for key variables in the model that control the aforementioned processes in order climatically to optimize yields under the climate changes (e.g., Gitay et al., 2001; Easterling et al., 2001). For example, the period from crop emergence to physiological maturity often is matched perfectly with the new growing season length that has been extended by climate change. Irrigation strategies are properly altered at exactly the moment the climate change begins to exert moisture stress, with water applications in precise amounts needed to correct for moisture deficit. These model simulations thusly are performed with climatically optimized adaptations, which provide the best possible crop yields under a given scenario of climate change. Issues concerning the rate of adoption of various adaptation strategies are ignored in such simulations. Some adaptations are climatically optimized within a growing season as a matter of current routine practice. Adjustment to irrigation scheduling to accommodate intra-seasonal moisture variation is an example; similarly for adjustment to pesticide and fertilizer applications. Those adjustments are farmers' hedges against climatic risk; the rate of adoption is not an issue with routine hedging. However, adaptations that involve change recognition, risk-taking or technical learning will take time to diffuse to all farmers. Change in the type of cultivar planted to tailor varietal traits of a crop to a changing environment is an example of an adaptation that will take time to spread.

We assert that the blanket application of adaptation under an optimization principle is a computational convention, which implicitly assumes that all farmers unerringly interpret the signal of climate change instantaneously, and infallibly respond with the correct adaptation strategies. We call this an assumption of *clairvoyance*. Clairvoyance assures the best possible crop yield outcome for a given scenario of climate change. It is the polar opposite of previous modeling studies that omitted adaptation altogether such that the negative impacts of climate change on crop yields are greatly overestimated (the so-called *dumb farmer scenario*).

Only a handful of researchers have confronted the question of timing of adaptation relative to the evolution of climate change (Kaiser et al., 1993; Schneider et al., 2000). Schneider et al. (2000) quantified the effect of clairvoyance by comparing the effect of adaptations, lagged behind the trajectory of climate change, on Great Plains corn yields versus the effect of clairvoyant adaptations. The time lag imposed an ignorance penalty on all farmers equivalent to 20 years of doing nothing in response to progressive climate change before the change was properly identified and the correct adaptation strategy applied. Adaptations perpetually tracked behind the climate change. The average corn yields in south central Minnesota, for example, under this lagged adaptation scenario were 4% lower than the clairvoyance adaptation scenario. While that difference may seem small, it represented a quarter of the total corn yield response under that particular climate change scenario.

2.1. INNOVATION DIFFUSION AND TECHNOLOGICAL SUBSTITUTION

The Schneider et al. (2000) analysis was informative of the discrepancy between clairvoyance and lengthy indecision, but it ignored the extensive theoretical and empirical literature on technology life cycles, innovation diffusion and technological substitution. Not *all* farmers likely are disposed to immediate action in the early stages of climate change. Smit et al. (1996) found that only 20% of southwestern Ontario farmers surveyed over a six-year period responded to observed climate variability with appropriate adjustments. This suggests that recognition of climate variability and change and the conscious decision to respond varies among farmers. Similarly, not *all* farmers likely are to do nothing until climate change has progressed substantially either. As noted above, some farmers will adapt early, the bulk of farmers will wait a little while before adapting, and a few will wait substantially longer than most.

Grübler's (1998) survey of technology and global change points out that innovation diffusion is a process by which a new idea, practice, or artifact spreads via different communication channels in time and space among members of a group. No innovation spreads instantly. Even though information about an innovation may diffuse very rapidly, the actual adoption usually takes much longer (Geroski, 2000). Moreover, innovations crucial to the establishment and maintenance of comparative advantage rarely evolve in a vacuum, but rather interact with existing practices and technologies. The adoption of these new technologies is referred to as technological substitution as opposed to adoption of pure new innovations.

The pattern of adoption of technological innovation/substitution over time is widely described as an S-shaped curve (or logistic curve), i.e., slow growth at the beginning followed by accelerating and then decelerating growth, ultimately leading to saturation. It follows the epidemiological model of diffusion (Mansfield, 1961; Geroski, 2000). A typical logistic curve is given by the following equation (adapted from Grübler, 1998):

$$f(t) = \frac{1}{1 + e^{-\alpha(t-t_0)}}\,, \tag{1}$$

where $f(t)$ is the fraction of technology growth to the upper limit, t denotes time, α is a coefficient characterizing the diffusion rate (the steepness of the S-curve), and t_0 denotes the inflection point at 0.5 of the total time to saturation (i.e., the point where the adoption/substitution growth rate reaches its maximum for a given innovation).

The logistic diffusion model is purely descriptive; it does not explain *why* the diffusion process takes this form, but it has proved robust in capturing the temporal pattern of diffusion across a range of technical innovations (Fisher and Pry, 1971). The governing forces that will prompt the production of adaptive technologies are assumed by the logistic diffusion model but are not explicitly represented. Those forces include, for example, change in climate risk, factor prices, population, income, and other environmental and social conditions. In this research, we posit that agronomic adaptation to climate change is akin to technological substitution. Changes in agronomic practices in response to climate change are not a radically new innovation. They are, however, a change to an unfamiliar practice that will require time to diffuse to all farmers in a region. Not all farmers will decide that the climate has changed enough to warrant agronomic adjustments at the same time. Many factors (e.g., climate variability, social and economic events) are likely to influence the parameters of the logistic diffusion process. However, the literature (assayed by Grübler, 1998) suggests that the uptake of new agronomic adaptive strategies by farmers under most conditions can be expected to follow some variant of the basic functional form of the logistic diffusion model.

The logistic diffusion model is not straightforward to implement using the results of crop process model simulations. Because each unique application of a crop process model can only represent one farmer's behavior or a group of farmers with the same behavior, no single model run can capture the entire spectrum of farmer adoption behaviors in a region with respect to a given duration and amount of climate change. Without a principle guiding the allocation of adaptation strategies among multiple model runs, the results are, as alluded to above, *ad hoc.* So the question we address in this research is how to capture a mix of farmer adaptation behaviors in an ensemble of runs of the same model in order to simulate a logistic diffusion process. Our approach to answering this question is presented in Section 3.3.

3. Methodology

This research is part of a large integrated assessment modeling study that seeks to understand the implications of climate variability and change for biophysical productivity and associated economic welfare for a region that covers most of the southeastern United States (Mearns et al., this issue). One of the unique features of the larger project in which this is embedded is its use of high-resolution climate change scenarios produced by nesting the RegCM2 limited area climate model inside the CSIRO general circulation model discussed fully in Mearns et al. (this issue). The climate data and climate model outputs used here in this research were gridded at a resolution of $0.5° \times 0.5°$, resulting in 420 grid boxes. The location of the grid is shown in Figure 1. Separate crop model runs described below were performed at each grid box.

3.1. EROSION PRODUCTIVITY IMPACT CALCULATOR (EPIC)

The model used to evaluate agronomic adaptations to climate change (with rising atmospheric CO_2 levels) was the Erosion Productivity Impact Calculator (EPIC, Williams et al., 1984; Williams et al., 1989). EPIC is a crop simulation model developed to estimate the relationship between soil erosion and crop productivity (Williams et al., 1984). In addition to including routines for soil erosion and plant growth, the model includes components for weather simulation, hydrology, nutrient cycling, plant growth, tillage and crop management. EPIC operates on a daily time step.

Figure 1. Study area and grid.

Among factors simulated by EPIC are evapotranspiration (based on the Penman–Monteith model), soil temperature, crop potential growth, growth constraints (water stress, stress due to high or low temperature, nitrogen and phosphorus stress) and yield. EPIC uses a single model for simulating all crops, although of course, each crop has unique values for model parameters. The crop growth model relies on radiation-use efficiency to calculate photosynthetic production of biomass. The potential biomass is adjusted daily for stress from the following factors: water, temperature, nutrients (nitrogen and phosphorus), aeration and radiation.

Atmospheric CO_2 concentrations in EPIC influence photosynthesis by modification of the radiation-use efficiency term. They also influence water use efficiency by modification of the stomatal conductance term in the equation of evapotranspiration. Crop-specific functions were developed by solving response curves of radiation-use efficiency versus CO_2 from the literature. We define water use efficiency as the ratio of crop yield to actual evapotranspiration (Easterling et al., 1992b). The CO_2 fertilization algorithm in EPIC was modified by Stockle et al. (1992) to account for the interactive effects of vapor pressure deficit (VPD) and increased CO_2 on radiation-use efficiency. The higher the VPD, the lower is the positive effect of CO_2.

For this study CO_2 concentrations are initialized at 330 ppm (baseline ambient level) and then allowed to increase in intervals of 17.5 ppm with each step of climate change (discussed below) to a final concentration of 540 ppm. Crop yields are estimated by multiplying the above-ground biomass at maturity (determined by accumulation of heat units or specified harvest date) by a harvest index (crop yield divided by above ground biomass) for the particular crop.

EPIC requires data on soil physical properties (for example, bulk density, water-holding capacity, wilting point) and management (for example, fertilization, tillage, planting, harvesting, irrigation). The weather variables necessary for driving the EPIC model are daily values of precipitation, minimum/maximum air temperature, solar radiation, windspeed and relative humidity. A detailed discussion of EPIC input data attributes unique to this study comes in the next subsection.

EPIC has been subjected to numerous validation exercises. Extensive tests of EPIC simulations were conducted at over 150 sites and on more than 10 crop species and generally those tests concluded that EPIC adequately simulated crop yields (Kiniry et al., 1990; Rosenberg et al., 1992). Easterling et al. (1996) specifically validated the EPIC yield predictions during recent episodes of climate extremes that emulate expected attributes of climate warming in the Great Plains.

3.2. EPIC INPUT DATA FOR THIS STUDY

3.2.1. *Soil Data*

The State Soil Geographic (STATSGO) database (USDA, 1994) was used with a geographic information system to determine the *dominant* soil (defined as the most extensive soil) for each of the different grid scales. The STATSGO soil association maps are compiled from generalized soil survey maps at 1:250,000 scale. The STATSGO data are divided into map units with a minimum resolution of 625 hectares, which can contain up to 21 soils. The percentage of each soil is known within each map unit but its distribution within each map unit is not known. Therefore the *dominant* soil is only an estimate since a map unit is not necessarily totally contained within a grid cell. STATSGO also lists a prime farmland classification for each soil. This classification rates farmland from 0 to 9 based on soil and climatic properties and was used to determine the *dominant* soil type depending on what crop was being modeled in an area. Only soils with the rating of prime farmland were considered for maize, soybeans, and wheat.

3.2.2. *Climate Data and Climate Change Scenario*

The baseline climate was compiled from 1960–1995 daily observations of maximum/minimum temperature, precipitation, radiation, relative humidity and windspeed (described in Mearns et al., 2003, this issue). The climate change scenario of the RegCM limited area climate model is described more fully in Mearns et al. (2003). The larger project that incorporates this research developed climate change scenarios at both low resolution (general circulation model) and high-resolution (limited area model nested within a general circulation model) scales. The rationale for the climate models used in this research appears in Mearns et al. (2003). Because this research does not examine issues of spatial scale directly, we elected to use the high-resolution scenario only. This decision was also supported by previous research that concluded that the additional spatial detail of high-resolution climate change scenarios adds regionally-detailed information to adaptation analysis not available with the use of low-resolution scenarios (Easterling et al., 2001).

A major challenge in constructing our methodology was the development of a time-evolving climate change scenario derived of an equivalent doubling of atmospheric CO_2 equilibrium solution. Our test of logistic adaptation required a time-evolving climate change scenario. By dividing the RegCM $2 \times CO_2$ climate change into 12 equal fractions we created a 'mock' transient (time-evolving) climate change scenario. Each of the 1/12 segments of climate change (temperature, precipitation, relative humidity, windspeed, solar radiation) was used to adjust the 1960–1995 baseline daily climate following standard procedures (described fully in Mearns et al., 2003, this issue). While we recognize that changes in climate variability caused by mean changes in climatic elements using this scheme are crucial to agricultural production, we do not analyze the effects of change in variability on adaptation of crops *per se* in this paper. This is a recognized deficiency of this research and is being addressed explicitly in follow on research.

The projection of future rates of increase in atmospheric CO_2 and resulting climate change is a matter of speculation and debate. For purposes of discussion only, we assume that it takes 60 years to reach the $2 \times CO_2$ climate change. Hence, each of the 12 fractions represents 5 years of climate change. To simplify reporting of the results of our crop modeling, we convert the resulting 12 5-year yield simulations into three 20-year means (1/3, 2/3, 3/3). Shorter intervals than 20 years do not allow adequate time for distinguishing the dynamic effect of climate change on adaptation. The obvious lack of realism in this approach is compounded by an implicit assumption of a linear trajectory of climate change.

The RegCM climate changes (temperature and precipitation) are summarized for the corn growing season (April–August) in a set of maps (Figures 2a–c, 3a–c). The changes varied widely across the Southeast (Figures 2a–c, 3a–c). In general, the southwestern portions of the region became slightly warmer and much wetter. The northeastern portions became much warmer and much drier. A positive temperature gradient extended generally from the less warm southwestern quadrant to the much warmer northeastern quadrant of the region. In the first 20 years of change (Figure 2a), the warming was greatest along the eastern seaboard where the temperature increase of several grid boxes averaged as much as 2.1 °C. A small, isolated area of large temperature increase is discernable in southern Louisiana. Most of the area of the Gulf States and the Appalachian Mountains showed little or no warming in this early period. The spatial distributions of warming generally were maintained throughout the latter two thirds of the climate change, with the warming intensifying everywhere (Figures 2b,c). By the third 20 years of climate change, large parts of the eastern seaboard states had warmed by a average of up to 6.3 °C while much of the southwestern part of the area had warmed little ($<$2.0 °C) if any.

The spatial distribution of RegCM precipitation changes was the mirror opposite of the temperature change distribution, with the largest decreases in all three periods distributed across the northeast quadrant of the region and the largest increases distributed across the southwest quadrant (Figures 3a–c). The areas of

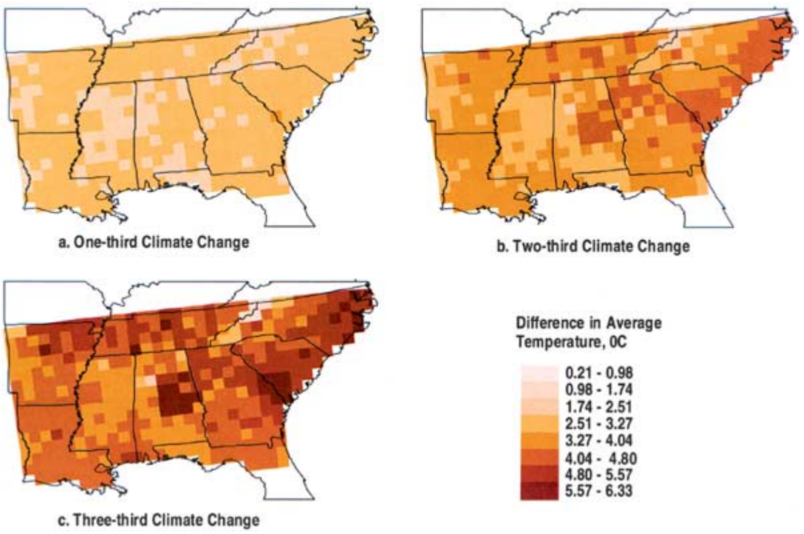

Figure 2. Change in temperature (°C) relative to 1960–1995 baseline climate simulated by the RegCM model. (a) 1/3 of 2 × CO_2 climate. (b) 2/3 of 2 × CO_2 climate. (c) 3/3 of 2 × CO_2 climate (or 'equivalent doubling CO_2 equilibrium').

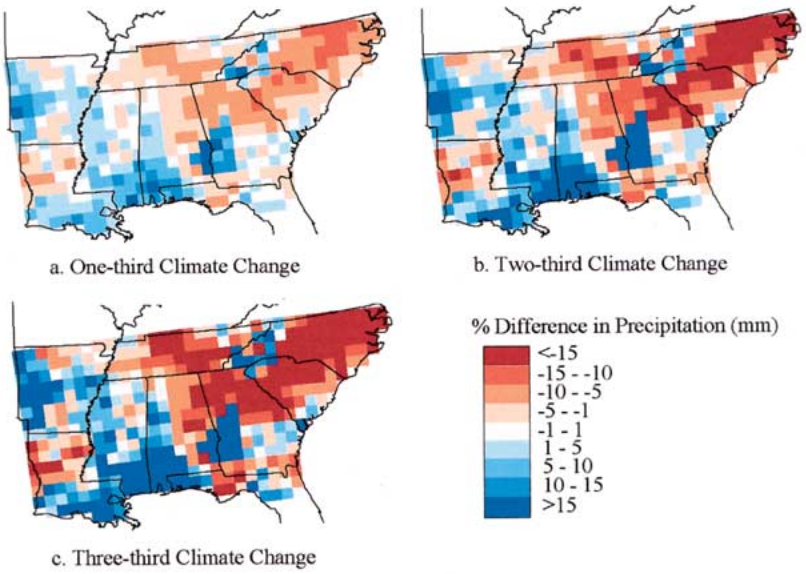

Figure 3. Change in precipitation (%) relative to 1960–1995 baseline climate simulated by the RegCM model. (a) 1/3 of 2 × CO_2 climate. (b) 2/3 of 2 × CO_2 climate. (c) 3/3 of 2 × CO_2 climate (or 'equivalent doubling CO_2 equilibrium').

largest decrease in precipitation lost more than 10% of total growing season rainfall while the areas of largest increase gained more than 15% of total growing season rainfall.

3.2.3. *Preparation of EPIC Representative Farms*

Representative EPIC farms developed by Brown and Rosenberg (1999) for major watersheds of the United States were adapted to the study region. Detailed profiles of relevant production characteristics (cultural practices, planting and harvesting dates, heat units required for maturity) were compiled for a selection of 'typical' farm enterprises across southeast. Although EPIC is capable of simulating many of the crop species grown in the southeastern U.S., we focus on corn only because it is the most extensively grown crop in the region, it is highly sensitive to climate stress, and it is responsive to agronomic management. For the purpose of testing our methodology, one crop is adequate. However, we recommend that other crops, some in rotation, be tested in subsequent research. Representative farms data were gridded such that a single farm enterprise growing corn was positioned at the centroid of each grid box.

3.3. PROCEDURES

Four different adaptation scenarios (including no-adaptation) were constructed to capture the range of possibilities of farmer response to climate change in the EPIC model. They include: (1) *clairvoyant*; (2) *lagged*; (3) *logistic*; and (4) *no-adaptation.*

3.3.1. *Clairvoyant Adaptation*

As noted above, clairvoyant adaptation occurs when all farmers instantly recognize and correctly respond to climate change. EPIC was modified to represent clairvoyant adaptation by optimizing planting dates and cultivar growing season lengths in synchrony with the evolving climate change. The results are interpreted as the 'best case' of adaptation and consonant with the majority of adaptation modeling studies in agriculture.

3.3.2. *Lagged Adaptation*

Lagged adaptation occurs initially when all farmers fail to recognize climate change until 10 years (two 5-year increments of climate change) have elapsed and then they all adapt in unison optimally with respect to the average climate of those 10 elapsed years. From that point on, the farmers remain one full 10-year step behind the current 5-year increment of climate change as they traverse the entire 60 years of climate change. Thus, farmers are assumed to behave as though they fail to recognize the climate change or refuse to believe that the change warrants action for 10 years. EPIC was modified to represent lagged adaptation by optimizing planting dates and cultivar growing season lengths to the average climate of the 10 years prior to the current 5-year increment of climate change. We recognize that few if any farmers are likely to experience 10 years of steady climate change without adapting. However, we deliberately chose a lag that is at the outer bound of failure to act. Clearly, the results are to be interpreted as the 'worst case' of adaptation (save no adaptation at all) and, together with the clairvoyant case, bound the envelope of adaptation.

3.3.3. *Logistic Adaptation*

The logistic curve (Equation (1)) is used to allocate the fraction of farmers, $f(t)$, who adopt changes in planting dates and varietal strains at time t relative to the onset of a 5-year segment of climate change. This assumption stipulates that a small fraction of farmers adapt immediately to the first and each subsequent 5-year segment of climate change. Those early adaptors (f_1) are followed by a larger subgroup of early middle adopters (f_2) that delays adaptation for 10 years and remain 10 years behind in each of the subsequent 5-year segments of climate change. Subgroup f_2 is followed by another large subgroup of late middle adopters (f_3) that delays adaptation for 15 years and remains 15 years behind. Finally, a small subgroup of laggards (f_4) delays adaptation for 20 years (i.e., it begins adaptation at the beginning of the fourth 5-year segment of climate change) and remains 20 years behind. Hence, it takes the first 20 years of climate change for all farmers to begin to adapt. Thereafter, all farmers adjust with each new 5-year segment of climate change, but at the lag times f_1–f_4 specified above. The proportion of farmers allocated among f_1–f_4 in the hypothetical fifth 5-year time slice (years 25–30) is shown in Figure 4 according to Equations (2)–(5) below.

We recognize that issue can be taken with the length of time assumed for cultivar adaptation to be fully adopted (20 years); however, the literature suggests large variation in times required for full adoption of agricultural innovations ranging from 10 years for fertilizer application to 30 years for the full adoption of a new crop species such as soybeans (Reilly, 1995). By lagging 20 years behind the current climate changes, the latter subgroup f_4 consists essentially of non-adaptors who misread the signal of climate change for a variety of reasons ranging from poor knowledge to rigid adherence to tradition. Although we do not explicitly account for farm failure, we presume that this latter group would have a large attrition rate due to inefficient response to climate change. However, it is reasonable to expect that there will be replacement within this subgroup; moreover, we assert that each subgroup will be replenished with new generations of farmers through time, thus maintaining the logistic form of adaptation.

This procedure causes adaptation to begin slowly with relatively few farmers adapting, followed by rapidly increasing numbers adapting less efficiently until the rate slows as full saturation of adaptation at varying degrees of efficiency is achieved by the end of the 20-year cycle.⋆ This sequence is explicit in Figure 5,

⋆ Or 1/3 of the climate change that is expected from an equivalent doubling of atmospheric CO_2, which is assumed to be reached in 60 years.

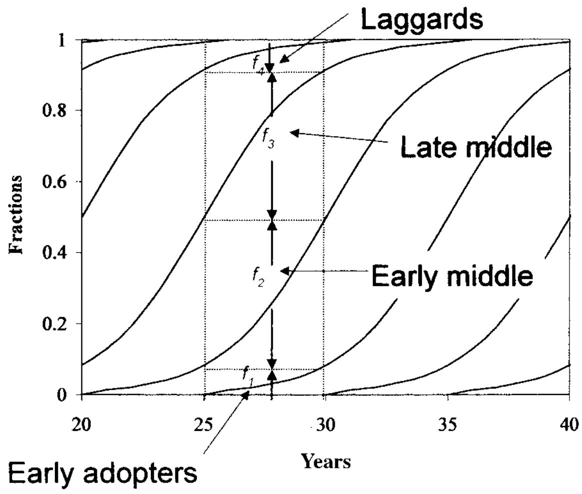

Figure 4. Logistic adaptation: Illustration of fraction of farmers (f) adapting to climate change during hypothetical period years 25–30. A small fraction of farmers (f_1) adapts immediately. Farmer fractions f_2, f_3, and f_4 adapt early middle, late middle and lagged, respectively. The fractions for f_1–f_4 can be derived from Equation (2), and the sum of f_1–f_4 equals 1.

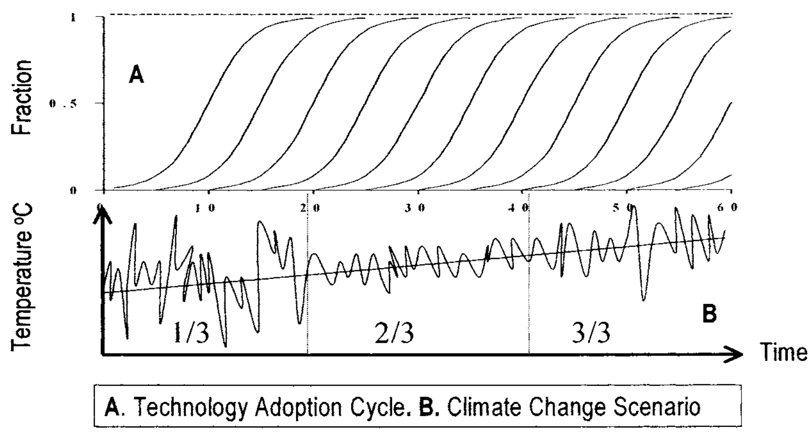

Figure 5. Technology substitution cycles (a) with hypothetical transient climate change (b).

which shows hypothetical 5-year waves of adaptation in the upper panel (A) versus a hypothetical transient climate change in the lower panel (B). In our case, we assume that a technology cycle spans 20 years, we get: $t_0 = 10$, and $\alpha = 0.48$ (see Appendix I for detailed procedures to calculate t_0 and α). Again, the logistic curve describing a full 20-year cycle is approximated by three 5-year computational time-steps. Adaptation cycles overlap, allowing for new adaptation to take place before previous cycles are complete (Figure 5). Such allows continual adjustment to adaptation in 5-year time steps but with varying degrees of efficiency among the subgroups f_1–f_4.

We use a matrix approach to combine model simulations at each of the 5-year time steps. Let **F** represent the matrix of fraction of farmers falling into the classes of clairvoyant (f_1), early middle (f_2), late middle (f_3) and lagged (f_4) adaptors, and $\mathbf{Y}_{yld}$, represents the matrix of yields from model simulations run with clairvoyant (y_{clv}), early middle (y_{ea}), late middle (y_{la}) and lagged ($_{lag}$) adaptations, respectively. A mean yield for logistic adaptations ($Y_{logistic}$) at a given 5-year step can be calculated from the following set of equations (Equations (2)–(5)). The elements f_i of **F** can be calculated from Equation (2). The elements of $\mathbf{Y}_{yld}$ (i.e., y_{clv}, y_{ea}, y_{la}, and y_{lag}) can be obtained from EPIC runs for each 5-year-step for adaptations discussed above.

$$fi = \int_{(i-1)*5}^{i*5} f'(t)dt \,, \tag{2}$$

where $f'(t)$ is the derivatives of Equation (1) and $i = 1, 2, 3, 4$.

$$\mathbf{F} = [f_1, f_2, f_3, f_4] \tag{3}$$

$$\mathbf{Y}_{yld} = [\mathbf{y}_{clv}, \mathbf{y}_{em}, \mathbf{y}_{la}, \mathbf{y}_{lag}] \tag{4}$$

$$\mathbf{Y}_{logistic} = \mathbf{F} * \mathbf{Y}^{-1}. \tag{5}$$

Four simulations are done for each grid box within a 20-year technology substitution cycle (assumed 20 years), meaning that the EPIC model was run in a 5-year interval, and a total of 12 runs were done for the entire period under study. As noted above, results are averaged over 20-year time periods and reported thusly.

3.3.4. *No Adaptation*

The no adaptation case is the industry standard for the so-called ‘dumb farmer’ scenario. The EPIC model is run with climate change using current technology and no agronomic adjustment, as if the farmer was oblivious to climate change. It is the least realistic of the scenarios, but we include it because it remains an assumption of a majority of the crop modeling studies in the literature and, thus, serves as a useful benchmark for comparison of our results (Gitay et al., 2001).

3.3.5. *Analytical Protocol*

Corn (maize) yields were simulated with the baseline climate and the ‘mock’ climate change at each grid box. The three different strategies of adaptation (clairvoyant, lagged, logistic) are compared with the no-adaptation case in order to evaluate the relative ameliorative effect of each strategy on simulated yields. First, we examine the mapped spatial distribution of climate change-induced yield changes under the three strategies of adaptation relative to yields simulated with the baseline climate. Second, we examine the mean yield changes under the three strategies aggregated to the levels of states in the region and then the entire study region. Third, we investigate the statistical significance of those yield changes using analysis of variance.

4. Results

4.1. SPATIAL DISTRIBUTION OF YIELD CHANGES

The spatial distribution of changes in corn yields (% of baseline yields at each third of climate change) for the four adaptation scenarios (no adaptation, clairvoyant, lagged, and logistic adaptation) generally tracked the distribution of the climate changes described above (Figures 6a–d, 7a–d, 8a–d). In the first 20 years (1/3 climate change), yield losses of up to –10% with no adaptation covered most of the northern half of the region while the southern half generally experienced yield gains of up to 10% (Figure 6d). As expected, clairvoyant adaptation was most effective in abating yield loss (Figure 6a), while lagged adaptation was least effective (Figure 6b). Clairvoyant adaptation almost totally eliminated yield losses in the first 20 years of climate change although it did not seem to stimulate yield gains beyond those of the no adaptation case. The pattern of yield change with logistic adaptation was indistinguishable from the lagged adaptation case and not as effective as clairvoyant adaptation (Figure 6c).

As the climate changes intensified in the second (2/3 climate change) and third (3/3 climate change) 20 years, the effectiveness of adaptation in terms of slowing the southward expansion of yield loss converged toward small differences (Figures 7a–d, 8a–d). In the no adaptation case, yield losses intensified in the north and spread southward during the 2/3 and 3/3 climate change. In the final 20 years of climate change, large clusters of grid boxes in the northern tier of the region experienced yield losses up to –40% regardless of adaptation scenario (Figures 8a–d). All three adaptation scenarios abated yield losses in the southernmost part of the region, with clairvoyant adaptation being most effective in promoting yield gains in that portion of the region (Figures 8a–d). The pattern of yield changes with logistic adaptation was virtually indistinguishable from lagged adaptation. The most important distinction in the distribution of yield changes between logistic and clairvoyant adaptation seems to be the larger degree to which the positive effects of climate change are assisted by clairvoyant adaptation than by logistic adaptation.

4.1.1. *Mean Yields for States*

Regional assessments of the impact of climate change often require state or provincial level information. Yields from each of the adaptation scenarios are presented as state-level percentages of baseline yields averaged over all three increments of climate change (Figures 9 and 10). The spatial variability seen in the mapped distributions is evident in the state-level means. Of the eight states in the study region, seven of them (Alabama, Georgia, Mississippi, Arkansas, North Carolina, South

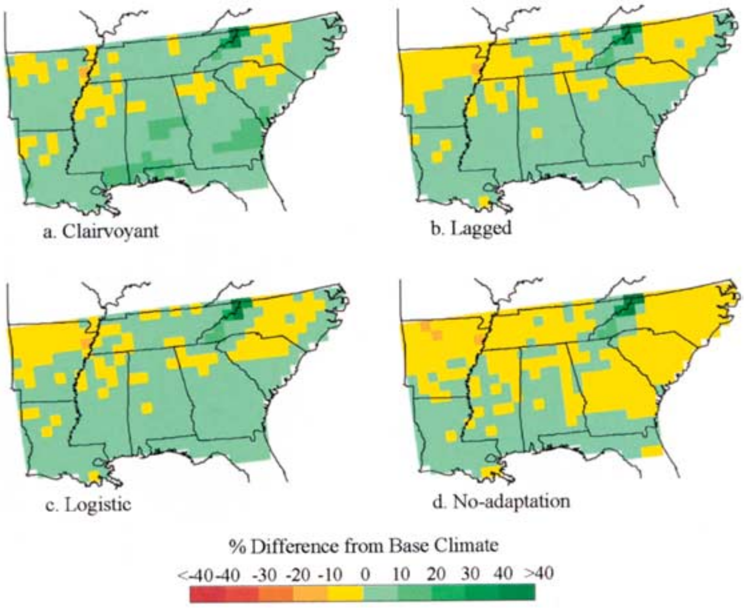

Figure 6. Response of corn yields (% of 1960–1995 baseline yields) to 1/3 of RegCM 2 × CO_2 climate change. (a) No adaptation. (b) Clairvoyant adaptation. (c) Lagged adaptation. (d) Logistic adaptation.

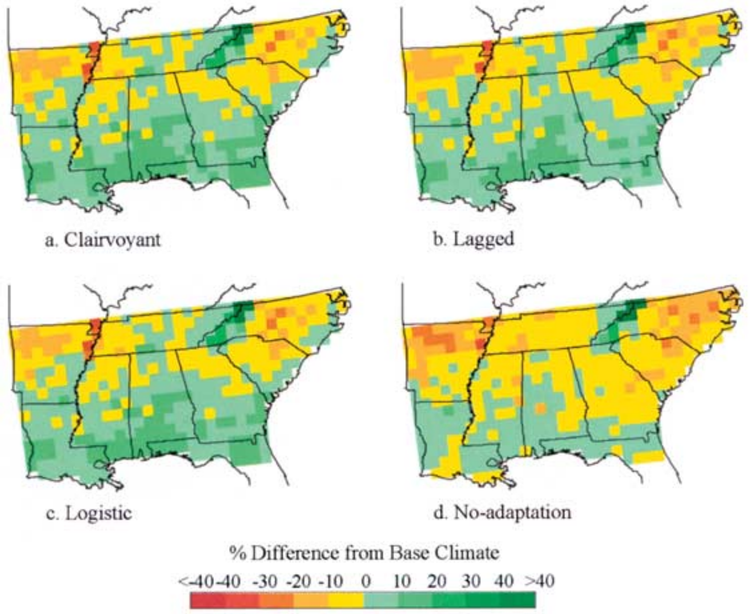

Figure 7. Response of corn yields (% of 1960–1995 baseline yields) to 2/3 of RegCM 2 × CO_2 climate change. (a) No adaptation. (b) Clairvoyant adaptation. (c) Lagged adaptation. (d) Logistic adaptation.

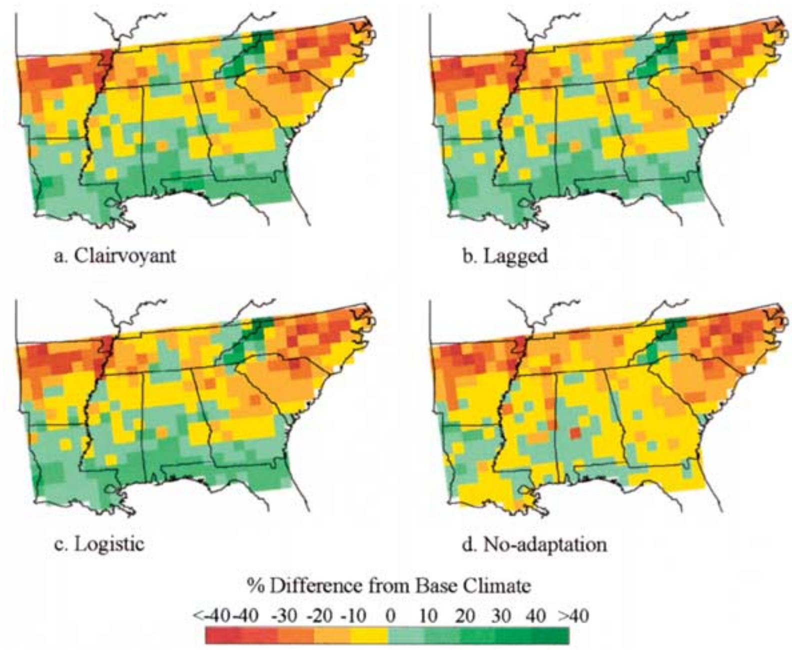

Figure 8. Response of corn yields (% of 1960–1995 baseline yields) to 3/3 of RegCM 2 × CO_2 climate change. (a) No adaptation. (b) Clairvoyant adaptation. (c) Lagged adaptation. (d) Logistic adaptation.

Carolina, and Tennessee) experienced yield losses relative to the baseline when no-adaptation is modeled (Figures 9 and 10). The exception is Louisiana. Each of the adaptation strategies (clairvoyant, logistic, and lagged) ameliorates at least a portion of the yield loss in all states. In four of the states (Alabama, Georgia, Mississippi, and Louisiana), all of the adaptation strategies show an increase in yield (Figures 9a–d). These states experienced yield gains of 4–7% with clairvoyant, 2–5% with logistic adaptation, and 1–4% with lagged adaptation. Although lagged adaptation was not as effective as clairvoyant adaptation, it clearly improved yields relative to the no-adaptation case.

However, none of the adaptation strategies could reverse the negative effects of the climate change (Figures 10a–d) in the northern part of the study region (Arkansas, North Carolina, South Carolina, and Tennessee). Here the yield loss ranges from –1% to –6% depending on the adaptation strategy.

4.2. MEAN CORN YIELD CHANGES ACROSS THE STUDY AREA

We posit that the effect of the technique used to model agronomic adaptation of corn yields to climate change on outcomes can be evaluated usefully at the scale of the entire southeastern U.S. We average the yields simulated with each adaptation strategy over all grid boxes to reach an overall mean for the study area. At each

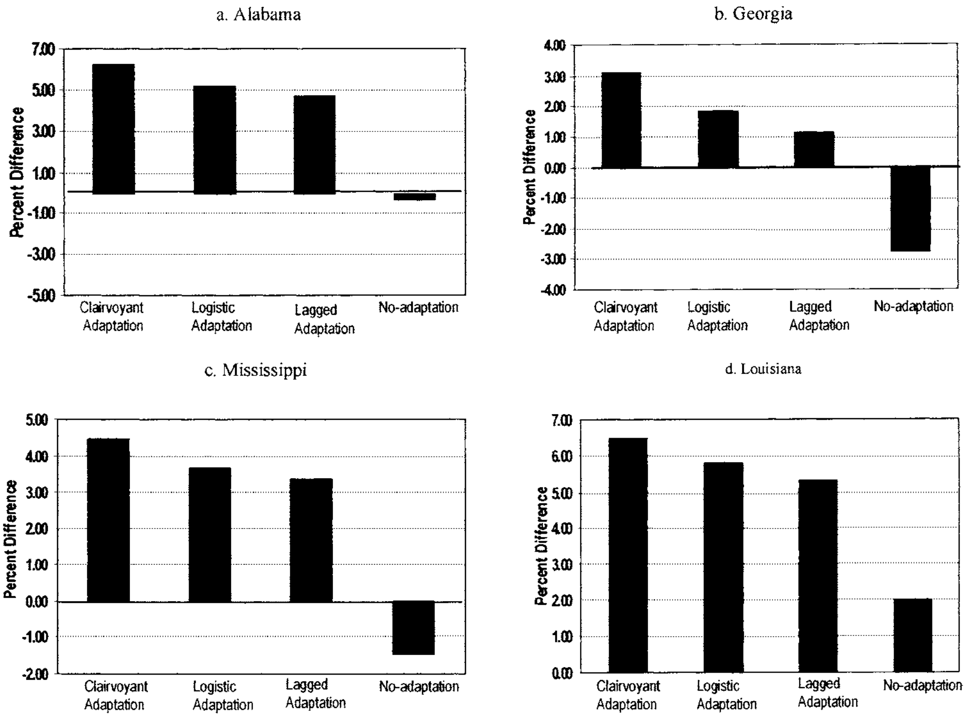

Figure 9. Mean response of corn yields (% of 1960–1995 baseline yields) over all three thirds of RegCM climate change in selected states. (a) Alabama. (b) Georgia. (c) Louisiana. (d) Mississippi.

third of climate change, we compare the mean yield for the no-adaptation strategy with the baseline (no climate change) yields; then we compare the yields simulated with each adaptation strategy to the no-adaptation case. Finally we compare yields computed with each adaptation strategy to yields with every other adaptation strategy. The point to this exercise is to determine the extent to which the assumptions and procedures for representing adaptation influence the conclusions reached.

4.2.1. *No Adaptation versus Baseline Yields*

Mean yield response to climate change with no-adaptation was compared with mean yield response to the 1960–1995 baseline climate in order to establish a benchmark for the adaptation simulations. In the first 20 years (first third) of climate change, mean corn yields with no adaptation averaged –0.2% less than mean baseline yields (Table I). By the second 20 years (second third) of climate change, yields with no adaptation were –2.5% less than baseline yields. By the third 20 years (third third), they dropped to –6.9%. This trend shows that, on balance, the effect of the climate change was to reduce yields in spite of substantial gains in yield in much of the southern portion of the study area (Figures 6–8).

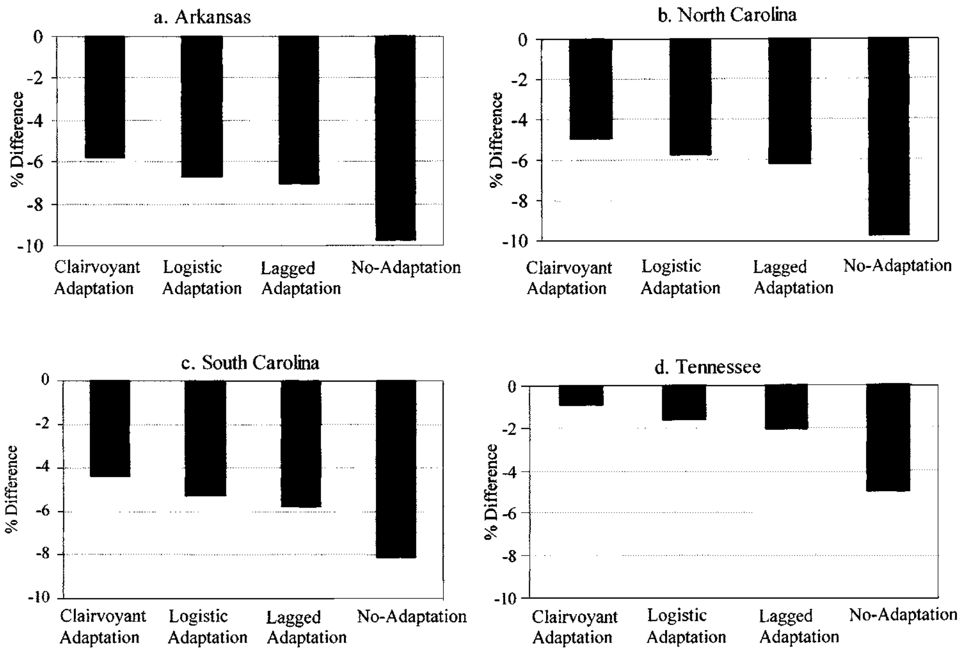

Figure 10. Mean response of corn yields (% of 1960–1995 baseline yields) over all three thirds of RegCM climate change in selected states. (a) Arkansas. (b) North Carolina. (c) South Carolina. (d) Tennessee.

Table I

Grid-wise mean corn (maize) yield response (% of baseline climate) to climate change scenarios for no adaptation case

Climate scenarios	Percent change in yield from baseline climate
Baseline climate	–
1/3 RegCM climate change	–0.2
1/3 RegCM climate change	–2.5
1/3 RegCM climate change	–6.9

4.2.2. *Each Adaptation Strategy versus No Adaptation*

Yields simulated with each adaptation strategy were compared with the no-adaptation yields to determine adaptive success. Multi-way analysis of variance was performed to determine the statistical significance of yield differences between the adaptations and the no-adaptation cases at each third of climate change. We report yield differences as being significant at both the $\alpha = 0.05$ level and the $\alpha = 0.10$ level.

Clairvoyant adaptation, as expected, was most effective in improving yields relative to the no adaptation yields at each of the three stages of climate change (Table II). Its success was greatest in the second 20 years of warming (6.2% greater than no adaptation) before settling back in the third 20 years to the same level as the first 20 years (5.0%). Lagged adaptation was least effective in improving yield losses at each of the three stages of climate change; it also experienced its best performance in the second 20 years of climate change (5.2% greater than no adaptation). Logistic adaptation was more effective than lagged adaptation in the first two thirds of climate change, but was indistinguishable from lagged adaptation in the latter third (Table II). It was less effective than clairvoyant adaptation all of the way through (Table II). Yield differences between the three adaptation strategies narrowed as the climate change progressed, suggesting that the effect of phasing of adaptation becomes less important as climate change intensifies. Yield differences between each of the adaptation strategies and the no adaptation case were significant at $\alpha = 0.05$ in all instances except logistic and lagged adaptation in the first 20 years of climate change. However, logistic adaptation was significant at $\alpha = 0.10$ (Table II).

4.2.3. *Intercomparison of Adaptation Strategies*

Intercomparison of adaptation strategies focuses on one of the major questions of the paper: Do the assumptions we used to model adaptation lead to significantly different yield outcomes? Specifically, is our posited ‘most realistic’ adaptation strategy (logistic adaptation) significantly different from the less realistic but more commonly used clairvoyant adaptation strategy?

The largest percentage difference in yields was between clairvoyant and lagged adaptation strategies (2.8%, significant at $\alpha = 0.05$) in the first third of the warming (Table II). This is not surprising because the underlying assumptions of those two strategies were most different. The largest percentage difference in yields between clairvoyant and logistic adaptation was also in the first third of the warming. Although that difference was not significant at $\alpha = 0.05$, it was significant at $\alpha = 0.10$. As noted above, the percentage differences between all of the adaptations diminished as the climate change strengthened (Table II). By the final 40 years of climate change (2/3–3/3), mean yields of none of the adaptation strategies were significantly different from each other (again, except for the no-adaptation case).

5. Discussion

The above results suggest that the yield outcomes modeled in this research are moderately affected by the assumption regarding timing of adaptation relative to the progression of climate change. The yield differences among adaptation strategies are most pronounced in the earliest stage (1/3) of the warming. In terms of

Table II

Comparisons of grid-wise mean corn (maize) yield (mT/Ha and %) between no adaptation, lagged adaptation, logistic adaptation, and clairvoyant adaptation in response to 1/3, 2/3, and 3/3 climate change

Climate/adaptation scenarios	Mean yield (metric tons per hectare)	% Change in yield from no-adaptation scenario	% Change in yield from lagged adapt. scenario	% Change in yield from logistic adapt. scenario
1/3 RegCM climate change				
No adaptation	6.670			
Lagged adaptation	6.809	2.1		
Logistic adaptation	6.845	2.6 [b]	0.5	
Clairvoyant adaptation	7.002	5.0 [a]	2.8 [a]	2.3 [b]
2/3 RegCM climate change				
No adaptation	6.514			
Lagged adaptation	6.852	5.2 [a]		
Logistic adaptation	6.859	5.3 [a]	0.1	
Clairvoyant adaptation	6.920	6.2 [a]	1.0	0.9
3/3 RegCM climate change				
No adaptation	6.218			
Lagged adaptation	6.503	4.6 [a]		
Logistic adaptation	6.499	4.5 [a]	–0.1	
Clairvoyant adaptation	6.530	5.0 [a]	0.4	0.5

[a] Difference is statistically significant at $\alpha = 0.05$ level.
[b] Difference is statistically significant at $\alpha = 0.01$ but not at $\alpha = 0.05$ level.

our logistic adaptation methodology, that is the time when a substantial proportion of the farmers have yet to take defensive agronomic action with respect to climate change. In terms of lagged adaptation, that is also the time in which even a smaller proportion of farmers have made a move to adapt than with the logistic adaptation strategy.

The narrowing of the differences in yields among the adaptation strategies as the climate change strengthened indicates the relatively large benefit of even sub-optimal adaptation. The small (0.5%) difference between clairvoyant and logistic adaptation in the final third of climate change demonstrates the value of sub-optimal adaptation – this is underscored by both sets of yields being significantly different from the no adaptation case (Table II). That is, optimal (clairvoyant) and sub-optimal (logistic) adaptation substantially improve the no-adaptation yields, but are, themselves, not much different. Similar comparison of lagged and clairvoyant adaptation strengthens the case (Table II). The explanation for this finding lies in baseline agronomic practices (current planting dates, varietal growing season lengths) that are far from climatically optimal. The representative farm information used to prepare EPIC was derived of Cooperative Extension circulars and personal communication from Extension Educators. That information reflects the fact that farmers do their best to cope with climate, but balance several factors that influence agronomic practice in addition to climate considerations. The net effect is that farmers are usually slightly out of kilter with the climate. Moreover, a reasonable expectation of farmers' behavior with respect to climate change is their growing awareness of the change and an accompanying desire to become more optimally adapted to it over time than in the present.

In spite of the narrowing differences between adaptation strategies over the course of climate change, clairvoyance remained the superior strategy for maintaining the highest corn yields under progressive climate change. It establishes an upper bound of the envelope of adaptive potential and also provides a rationale for monitoring and detecting long-term climate change, and the vigilance of farmers and their supporting institutions. The implication of no adaptation as the lower bound of the envelope of response needs little elaboration. This envelope is important because there is no guarantee that these results are robust across an ensemble of climate change scenarios and in fact the methods of this research need to be tested against a range of climate change scenarios.

As noted above, the degree to which farmer behavior with respect to climate change can be expected to remain sub-optimal is an open question. The results of this analysis, however, suggest that delayed farmer response causes two problems for a region. First, inability to properly recognize and take appropriate steps to deal apace with the climate change builds in inefficiency proportional to the time elapsed from the point at which climate change commences to the point at which proper adaptation occurs. Second, the adaptive behavior of some farmers in a region will perpetually lag behind the current state of the climate change, putting those farmers in a quasi-permanent state of less-than-optimal efficiency. This could indicate a social welfare problem that may or may not have market solutions.

Over the long time scales of this analysis, simple substitutions of existing agronomic practices in response to climate change (of the kind tested in this research) sooner or later will lose effectiveness in dealing with climate change. This can be seen in the declining effectiveness of all three adaptation strategies in the final third of climate change as heat stresses overcome the value of planting longer season varieties (Table II). New fundamental adaptive knowledge and technology will be required to cope with unprecedented climate challenges. Cultivars bred or genetically modified to deal with changing climate conditions better than current ones can be expected from the private and public research communities. Many of the new innovations that will be needed to deal with climate change are currently over the horizon and will be radically new to future farmers. Although the process that generates those innovations is beyond the scope of this paper, it is reasonable to expect that the uptake of those innovations will more likely follow the logistic pathway than the suite of agronomic substitutions tested here for the simple reason that it will take time for the innovations to gain farmers' trust.

6. Conclusion

Adaptation to climate change has become an important consideration in climate change impact research. According to the recent IPCC Third Assessment Report (Gitay et al., 2001), nearly a hundred studies globally investigate the effects of adaptation on agricultural impacts of climate change and the number is growing. Our assessment is that few studies of agronomic adaptations evaluate the effect that the method by which the adaptations are applied has on outcomes. This is problematic.

We hypothesized that the method used to simulate agronomic adaptation has the potential to influence yields in response to climate change sufficient to alter outcomes and challenge the robustness of further (economic) modeling dependent on those yields. In particular, we posit that our use of the epidemiological (logistic) model of technological substitution as a method of allocating agronomic adaptation is more realistic than current methods *a priori* and should give significantly different yield outcomes from optimization-based methods. Our tests of these propositions with corn in the southeastern United States were inconclusive. Logistic adaptation did not produce significantly different yield outcomes from those of the more commonly used clairvoyant adaptation, except at the very outset of the warming. However, it is important to point out that this research used one climate change scenario. A complete test will require multiple climate change scenarios, crops and geographic locations.

We conclude that our formulation of logistic adaptation provides a disciplined and theoretically (and empirically) sound basis for modeling adaptations relying on technological innovation and substitution. Such is an advance, although the degree to which logistic adaptation may provide different policy-relevant information from common practice remains an open question for future research.

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Appendix I: Procedures Used to Derive the Constants t_0 and α in the Logistic Equation

1. t_0 is the inflection point at 0.5 of the fraction. It is right half of the time span. In our case, the total time period is 20 years, so $t_0 = 10$.
2. α is a constant regulating the growth rate or the steepness of the S-curve. The rate of growth is the time derivative of the S-curve, and generally follows a normal distribution over time. Based on the time derivative of the S-curve with a maximum value of M, the growth rage (GR) at time t_0 is given by (Debecker and Modis, 1994):

$$\mathrm{GR} = \frac{\mathrm{M}\alpha}{4}. \tag{6}$$

A general normal density function can be given as following equation (Harnett, 1982).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(1/2)[(x-\mu)/\sigma]^2} \tag{7}$$

and the following factor can be derived from formula (12) by substituting μ for x.

$$f(\mu) = \frac{0.399}{\sigma}. \tag{8}$$

Since μ in formula (12) is identical to t_0 in Equation (11), and $f(\mu)$ in Equation (13) is identical to GR in Equation (11), therefore:

$$\frac{\mathrm{M}\alpha}{4} = \frac{0.399}{\sigma}. \tag{9}$$

According to the characteristics of the normal distribution, $\mathrm{P}(\mu - 3\sigma < x < \mu + 3\sigma) = 0.9974$, we know that 6σ will cover almost all the time period (99.74%). So in our case, we set $6\sigma = 20$ (total time period 20 years for one technology cycle), and we derive $\sigma = 3.333$. By substituting 1 (maximum fraction), 3.333 for M and σ in Equation (14), respectively, we get:

$$\alpha = 0.48.$$

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