Climate Change, Agriculture, and Water Quality in the Chesapeake Bay Region*

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Prepared for presentation at the
American Agricultural Economics Association Annual Meeting
Chicago, August 2001

* This research is sponsored by University Corporation for Atmospheric Research Subcontract S99-14918, *Climate Change, Agriculture, and the Environment*; U.S. Environmental Protection Agency Cooperative Agreement CR 826554-01-0, *Mid-Atlantic Regional Assessment*; U.S. Environmental Protection Agency Cooperative Agreement CR 82840701, *Mid-Atlantic Regional Assessment Phase II*; U.S. National Science Foundation Grant SBR-9521952, *Methods of Integrated Regional Assessment of Global Climate Change*; by U.S. Environmental Protection Agency Cooperative Agreement CR 824369-01, *GCC Impacts on Water Resources and Ecosystems*; and by U.S. Department of Agriculture Cooperative Agreement 43-3AEL-8-80058, *Agricultural Nonpoint Pollution Control: Environmental Policy Options and the Value of Information*.

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1. Introduction

Owing to the fundamental importance of food to human welfare and of climate to crop and livestock production, agriculture has been a focus of research on the impacts of climate change and variability. This research has been largely concerned with implications for the supply and cost of food and for producer incomes. Societal interest in agriculture is, however, much broader than these issues. Agriculture is a source of several positive and negative environmental externalities. Rural and urban populations in developed countries often value agricultural land as open space and as a source of countryside amenities. Agricultural land is also an important habitat for remaining wildlife species in many countries. These values are reflected in public programs in many countries to protect farmland from development and preserve particular types of agricultural landscapes. Agriculture is also a source of negative environmental externalities. Conversion of forest and wetlands to agricultural production is a major cause of deforestation and species loss in developing countries. In both developed and developing countries, nutrients, pesticides, pathogens, salts, and eroded soils are leading causes of water quality problems. On both the positive and negative side, agriculture can be both a sink and a source for greenhouse gas emissions.

Changes in environmental externalities from agriculture due to climate change may be more important from a public policy perspective than impacts on agricultural production, food prices, or farm incomes. Farmers—as well as seed companies, fertilizer distributors, and other firms that sell products and services to farmers—will have strong financial incentives to adapt to climate change by minimizing negative impacts on production and exploiting positive impacts. No one has any similar, direct financial stake in minimizing any negative environmental externalities from climate change or exploiting any positive externalities. It will be up to governments in each country to decide what environmental externalities are important enough to warrant action and what kinds of actions need to be taken to address these issues.

Several studies have been directed at the effects of climate change on the negative environmental externalities from agricultural production, including runoff (e.g., Chiew et al., 1995; Izaurralde et al., 1999; van Katwijk et al., 1993), leaching (e.g., Follett 1995), and erosion (e.g., Phillips et al., 1993; Williams et al., 1996). These studies excel at modeling the biological and physical relationships and processes underlying runoff, leaching, and erosion. However, they do not consider economic responses by farmers to climate change. Instead, they implicitly assume that farmers will continue to produce the same crops and livestock on the same land using the same management practices and technologies.

Changes in temperature, precipitation, and atmospheric carbon dioxide (CO_2) levels that affect the profitability of agricultural enterprises could lead to changes in the amounts and locations of cropland and pasture land, the types of crops and livestock produced, and technologies and management practices for individual crops and livestock. These economic responses could give rise to “indirect” impacts of climate change on runoff, leaching, and erosion that could in principle augment, diminish, or even reverse the “direct” impacts assuming no economic responses on the part of producers.

The objective of this paper is to analyze the potential impacts of climate change on agriculture and water quality in the U.S. Chesapeake Bay Region for the year 2030, taking into account economic responses by farmers to climate change. To accomplish this objective we construct a simulation model of maize production in twelve watersheds within the Chesapeake Bay Region with economic and watershed components linking climate to productivity, production decisions by maize farmers, and nonpoint nitrogen loadings delivered to the Chesapeake Bay. Maize is an important crop to study because of its importance to the region's agriculture and because it is a major source of nutrient pollution. Maize is the most nitrogen-intensive of all major crops currently grown within the region. Livestock farms within the region also often dispose of manure on maize land.

We consider three climate scenarios: the present-day climate, which serves to establish a starting point; a scenario based on projections from the Hadley climate model for 2030; and a scenario based on projections from the Canadian Climate Centre (CCC) model for 2030. Because of huge uncertainties about the future of agriculture in the Chesapeake Bay region, even apart from climate change, we also consider two future baseline scenarios for the year 2030 designed to establish plausible upper and lower bounds on climate change impacts: a continuation of the status quo (SQ); and an "environmentally friendly," smaller agriculture (EFS). The climate and future baseline scenarios are described below.

2. The Chesapeake Bay Region

The Chesapeake Bay Region is a good case for study. The 165,000 square kilometer Chesapeake Bay watershed is the largest estuary in the United States (Chesapeake Bay Program, 1999). The watershed includes parts of the states of New York, Pennsylvania, West Virginia, Delaware, Maryland, and Virginia, as well as the entire District of Columbia. Over 15 million people currently live in the Chesapeake Bay watershed.

The Chesapeake Bay is one of the most valuable natural resources in the United States. It is a major source of seafood, particularly highly valued blue crab and striped bass. It is also a major recreational area, with boating, camping, crabbing, fishing, hunting, and swimming all very popular and economically important activities. The Chesapeake Bay and its surrounding watersheds provide a summer or winter home for many birds, including tundra swans, Canada geese, bald eagles, ospreys, and a wide variety of ducks. In total, the Bay region is home to more than 3,000 species of plants and animals (Chesapeake Bay Program, 1999).

Human activity within the Chesapeake Bay watershed during the last three centuries has had serious impacts on this ecologically rich area. Soil erosion and nutrient runoff from crop and livestock production have played major roles in the decline of the Chesapeake Bay. The Chesapeake Bay Program (1997) estimates that agriculture currently accounts for about 39% of nitrogen loadings and about 49% of phosphorus loadings in the Chesapeake Bay. This makes agriculture the single largest contributor to nutrient pollution in the Chesapeake Bay. Other contributors include point sources such as wastewater, forests, urban areas, and atmospheric deposition.

The locations of the twelve watersheds analyzed here within the Chesapeake Bay region are shown in Figure 1. The watersheds all lie within the state of Pennsylvania, and are identified by the 3-digit codes shown in Figure 1. Table 1 provides statistics for the twelve watersheds on land area, maize production, nitrogen applications for maize, and nonpoint nitrogen loadings from maize production delivered to surface waters generally and to the Chesapeake Bay in particular. The nitrogen application statistics include both inorganic fertilizer and animal manure. The statistics are derived from the economic and watershed models described below. The statistics on nonpoint loadings represent deliveries to surface waters and exclude deliveries to groundwater. Groundwater contamination from fertilizers and pesticides is an important concern in many areas, but it is beyond the scope of this paper.

For the twelve watersheds as a whole, maize accounts for approximately 4% of land use but 30% of total nonpoint nitrogen loadings delivered to surface waters. This percentage rises to approximately 67% if one excludes atmospheric deposition, a major source of nonpoint loadings in the Chesapeake Bay region. Atmospheric deposition must ultimately originate somewhere. Nizeyimana et al. (1997) estimate that crop and livestock production account for 37% of nitrogen oxides (NO_x) and 97% of ammonia (NH_4) in the atmosphere of Pennsylvania watersheds.

3. Economic Model

The simulation model of maize production in the Chesapeake Bay Region has economic and watershed components linking climate to productivity, production decisions by maize farmers, and nonpoint pollution loadings. The economic model predicts the choices that farmers make with respect to the amount of land devoted to maize and the usage of fertilizer and other inputs into maize production. Precipitation, temperature, and atmospheric CO_2 levels affect the uptake of nutrients and the productivity of land used in maize production. The economic model is based on previous models we constructed to examine nonpoint agricultural pollution (Abler and Shortle, 1995, 1996, 1997; Shortle and Abler, 1997).

We begin with an expected cost function for maize. We use an expected cost function rather than the actual cost function because the weather (temperature and precipitation) in our model is random and because farmers make production decisions at the beginning of the growing season, before the actual weather is known (Just, 2000). Farmers base their production decisions on the distributions of the random temperature and precipitation variables, which they are assumed to know.

The expected cost function for maize is a two-level constant-elasticity-of-substitution (CES) function that exhibits constant returns to scale at each level. At the upper level, maize is produced from a composite mechanical input and a composite biological input. Mechanical inputs provide the power needed for tasks such as planting, weeding, and harvesting, while biological inputs provide nutrients and a growth environment. The lower levels generate the composite inputs. The mechanical input is produced from capital and labor, while the biological input is produced from land and fertilizer. The two-level CES production function is parsimonious in parameters and represents a reasonable approximation at an aggregate level to agricultural production processes (Hayami and Ruttan, 1985).

The expected cost function for maize (C^e) in the j th watershed can be written as

$$C_j^e = \Gamma_j \left[a p_M^{1-s} + (1-a)\left(\frac{u_j^0}{u_j^e}\right) p_j^{\,1-s} \right]^{1/(1-s)} Y_j^e, \tag{1}$$

where Γ_j is a constant chosen for each watershed so that the model reproduces base-period statistics, a is a distributive share parameter, s is an elasticity of substitution, p_M is the shadow price of the mechanical input (a composite of capital and labor), p_j is the shadow price of the biological input (a composite of fertilizer and land), u_j^e is the expected level of climate productivity (defined below), u_j^0 is the initial (base-period) expected level of climate productivity, and Y_j^e is planned output.[1]

The shadow price of the mechanical input is:

$$p_M = \left[m\left(\frac{p_K}{A_K}\right)^{1-h} + (1-m)\left(\frac{p_N}{A_N}\right)^{1-h} \right]^{1/(1-h)}, \tag{2}$$

where m is a distributive share parameter, h is an elasticity of substitution, p_K is the rental rate on capital, p_N is the wage rate for labor, A_K is the level of capital-augmenting technical change, and A_N is the level of labor-augmenting technical change. The shadow price of the biological input is:

$$p_j = \left[b\left(\frac{p_F}{A_F}\right)^{1-b} + (1-b)\left(\frac{r_j}{A_L}\right)^{1-b} \right]^{1/(1-b)}, \tag{3}$$

where b is a distributive share parameter, b is an elasticity of substitution, p_F is the price of nitrogen fertilizer, A_F is the level of fertilizer-augmenting technical change, r_j is the rental rate on maize land, and A_L is the level of land-augmenting technical change.

We assume that the rental rate on capital (p_K) and the wage rate (p_N) are exogenous. This is a reasonable assumption given that maize accounts for a negligible fraction of the Chesapeake Bay region's total demand for capital and labor. For similar reasons, we assume that the price of nitrogen fertilizer (p_F) and levels of factor-augmenting technical change are exogenous. We also assume that the output price (p) is exogenous, which is reasonable because maize production within the region is a negligible fraction of U.S. and global maize production. Labor is the numeraire and thus the wage rate is normalized to one. We set units of measurement so that p_K, p_F, r_j, and p are equal to one initially.

Several parameters and variables have the same values across watersheds. The watersheds are small and geographically contiguous, so that the production process for corn is very similar in each watershed. Farmers in each watershed also have access to essentially the same output and input markets. Rental rates on maize land can vary by watershed because land in some watersheds may be more productive when used for maize than land in other watersheds.

Maize output market equilibrium requires that farmers produce up to the point where the output price (p) equals expected marginal cost, which is equal to average cost because there are constant returns to scale:

$$p = \partial C_j^e \big/ \partial Y_j^e = C_j^e \big/ Y_j^e . \tag{4}$$

Because the output price is exogenous and all input prices are exogenous except the price of land, equation (4) can be used to obtain a solution for r_j. This solution represents the ex-ante (pre-growing season) rental rate on maize land.

The supply of land to maize production (L_j^s) is:

$$L_j^s = \ell_j z r_j^g \left(r_j^* \right)^x , \tag{5}$$

where ℓ_j is a constant scaling factor chosen so that equation (5) reproduces base-period land use statistics, z is a land supply shifter set to one initially (see below), g is the elasticity of maize land supply with respect to the rental rate on maize land, r_j^* represents the rental rate on land for alternative commodities that farmers could produce on the same land, and x is the elasticity of maize land supply with respect to the rental rate on land for alternative commodities. The rental rates r_j and r_j^* can differ from each other because of commodity-specific soil capital that makes a given hectare of land better suited for the production of some commodities than others (Orazem and Miranowski, 1994). Land market equilibrium requires land supply equal land demand. Given the solution obtained above for r_j, the land supply equation (5) gives a solution for the amount of land in maize, conditional on the value of r_j^*.

We do not model the production of alternative agricultural commodities. However, if these commodities are produced under constant returns to scale and if prices of non-land inputs into production are exogenous (for reasons given above in the case of maize), then a first-order Taylor series approximation to the relationship between the log of an output price index for alternative commodities (p^*) and the log of r_j^* is:

$$\ln p^* \approx s^* \ln r_j^*, \tag{6}$$

where s^* is the base-period factor share for land in the production of alternative commodities.[2] We set units of measurement so that both p^* and r_j^* are equal to one initially. Production of alternative commodities within the twelve watersheds is a small fraction of total national and global production, and so we assume that p^* is exogenous. Given this, equation (6) can be used to obtain a solution for r_j^*.

The derived demands for land (L_j) and nitrogen fertilizer (F_j) are given by Shephard's lemma:

$$L_j = \partial C_j^e \big/ \partial r_j , \tag{7}$$

$$F_j = \partial C_j^e \big/ \partial p_F . \tag{8}$$

Given the solutions obtained above for r_j and L_j^s, land market equilibrium ($L_j^s = L_j$) and the land demand equation (7) together give a solution for planned output (Y_j^e). This solution can then be inserted into equation (8) to find the amount of nitrogen applied to maize.

We scale climate productivity (u_j) so that it lies between zero and one. Given this scaling, it can also be interpreted as uptake, i.e., the fraction of nitrogen applied to maize that is taken up by maize plants. A convenient functional form is logistic:

$$u_j = \frac{1}{1+e^{-x_j}} , \tag{9}$$

where x_j depends on the weather and atmospheric CO_2 levels. We assume for ease of interpretation that x_j is linear in the logs of the weather and CO_2 variables:

$$x_j = v_j + f\ln\left(\frac{CO_2}{CO_2^0}\right) + \sum_i a_i \ln\left(\frac{\overline{Z_{ij}}}{\overline{Z_{ij}^0}}\right) + \sum_i e_i \ln\left(\frac{Z_{ij}}{\overline{Z_{ij}}}\right) + \sum_i m_i \ln\left(\frac{\overline{T_{ij}}}{\overline{T_{ij}^0}}\right) + \sum_i d_i \ln\left(\frac{T_{ij}}{\overline{T_{ij}}}\right). \quad (10)$$

The term v_j is a constant scaling factor chosen so that equations (9)-(10) reproduce the base-period uptake fraction (estimated at 0.7), CO_2 is the level of atmospheric carbon dioxide, $\overline{Z_{ij}}$ is the mean level of precipitation in time period i (i = 1, 2, 3, 4), Z_{ij} is the realized level of precipitation in time period i, $\overline{T_{ij}}$ is the mean temperature in time period i, and T_{ij} is the realized temperature in time period i. CO_2^0 is the base-period level of atmospheric carbon dioxide (under the current climate), $\overline{Z_{ij}^0}$ is the base-period value of $\overline{Z_{ij}}$, while $\overline{T_{ij}^0}$ is the base-period value of $\overline{T_{ij}}$. The parameters f, a_i, e_i, m_i, and d_i are elasticities.[3]

The four time periods are April-June (i = 1), July-September (2), October-January (3), and February-March (4). These periods were chosen on the basis of climate and maize production and fertilization patterns in the Chesapeake Bay region.

With the formulation in equation (10), changes in climatic means can have different effects on productivity than deviations from climatic means. This is intuitively reasonable because farmers, public- and private-sector agricultural R&D organizations, and others in the food and agricultural system can, given time, adjust to changes in climatic means in a way that they cannot adjust to short-term climatic shocks. These adjustments can include changes in the amounts and locations of cropland and pasture land, the types of crops and livestock produced, and technologies and management practices for individual crops and livestock.

The expected level of climate productivity (u_j^e), which is used in the expected cost function (1), is defined as the expected value of u_j. The weather in our model is random, while the level of atmospheric CO_2 is nonstochastic. Farmers are assumed to know the CO_2 level as well as the distributions of the stochastic precipitation and temperature variables.

An expected cost function of the type defined in (1) gives rise to a closed-form solution for planned output but not for actual output. Because production decisions are made in advance of the growing season, differences between planned output (Y_j^e) and actual output (Y_j) arise because of differences between expected climate productivity (u_j^e) and actual climate productivity (u_j). To solve for actual output we take a first-order Taylor series approximation to the log of actual output around the log of planned output:

$$\ln Y_j \approx \ln Y_j^e + l\left(\ln u_j - \ln u_j^e\right) + k_j. \tag{11}$$

We set the parameter l such that model, under the current climate and status quo (SQ) baseline scenario, reproduces the coefficient of variation for detrended Pennsylvania maize yields for the period 1950-2000.[4] The parameter k_j accounts for approximation errors in (11) and is set for each watershed so that the model reproduces base-period production statistics.

The values of the parameters in the economic model are shown in Table 2. Several of the parameters are the same between the status quo (SQ) and environmentally friendly, smaller agriculture (EFS) future baseline scenarios, while some are different. We discuss the differences below. Elasticities of substitution and land supply elasticities are based on Abler (2000), while factor proportions are based on U.S. Department of Agriculture (2000) and Huffman (1996). The parameters of the temperature and precipitation variables in the climate productivity equations (9)-(10) are based on ran time-series regressions for maize yields in the state of

Pennsylvania and cross-sectional regressions across U.S. states on maize yields. The results are not reported here for sake of conserving space.[5] We also relied on results from similar regressions for other states in Teigen and Thomas (1995). Some of the temperature and precipitation variables were not statistically significant in these regressions and so we set their elasticities equal to zero (these elasticities are not shown in Table 2).

The climate productivity elasticity with respect to the atmospheric CO_2 level (f) is based on Izaurralde et al. (1999). This reflects the so-called carbon dioxide "fertilization" or "enrichment" effect (Rosenzweig and Hillel, 1998). Elevated levels of atmospheric CO_2 can lead to an increase in photosynthesis and thus crop yields. They can also lead to a decrease in transpiration (evaporation from plant foliage), which reduces water stress during periods with little or no rainfall. There is some debate in the literature about whether CO_2 enrichment effects, which have largely been observed in the short term under controlled laboratory conditions, will be found over the long term under actual field conditions (see Rosenzweig and Hillel, 1998). We therefore also report simulation results in which there are no CO_2 enrichment effects ($f = 0$).

4. Watershed Model

Using the farmer decisions predicted by the economic model outlined above, the watershed model predicts deliveries of nitrogen to surface waters generally and to the Chesapeake Bay in particular within the twelve watersheds we examine here. The environmental model is based on the Generalized Watershed Loading Functions (GWLF) model (Haith et al., 1992). GWLF uses precipitation and temperature data, combined with data on land use, topography, and soil types, to estimate water runoff and pollutant concentrations flowing into surface waters from several types of land use, including maize. GWLF predicts both nitrogen and phosphorous loadings. However, we found that phosphorous loadings from maize production were very highly correlated with nitrogen loadings from maize production in each watershed. Thus, we focus here on nitrogen loadings.

Hydrologic models such as GWLF are too complex to be readily linked with an economic model. Rather than using GWLF directly, we followed Carmichael and Evans (2000), who applied Monte Carlo simulation techniques to GWLF and developed a dataset for each of the twelve watersheds that can be used to parameterize nitrogen loadings functions. They ran GWLF 1,000 times for each watershed under randomly drawn values for the allocation of land across three different categories (maize, other agriculture, and forests), nitrogen concentration in runoff, and precipitation. We used their data to parameterize GWLF according to the form

$$H_j = G_j + j_{3j} Z_j , \tag{12}$$

where

$$G_j = j_{1j} Z_j^2 R_j L_j + j_{2j} \left(Z_j^2 R_j \right)^2 L_j . \tag{13}$$

In equations (12)-(13), H_j is total loadings across all land use categories in the j th watershed as calculated by the GWLF model, G_j is loadings from maize, Z_j is the sum of precipitation during time periods 1, 2, and 3 (April-June, July-September, and October-January, respectively), L_j is land devoted to maize, and R_j is nitrogen concentration in runoff, as measured in mass per unit volume of water.

In the Monte Carlo simulations conducted by Carmichael and Evans (2000), land was allocated randomly across three different categories (maize, other agriculture, and forests), so that the total amount of land in these three categories was the same in each random sample. As such, the coefficients in equation (13) capture loadings due to putting land in maize above and beyond loadings that would be generated if the land were in other agriculture or forests.

The parameters j_{1j}, j_{2j}, and j_{3j} were estimated from the Carmichael and Evans (2000) datasets using ordinary least squares (OLS). The regression results are not presented in order to conserve space, but most cases each parameter was positive and statistically significant at the 1% level. In nine of the twelve watersheds the correlation coefficient between H_j and its predicted value from the regression equation ($\widehat{H}_j$) was more than 0.98.[6] In no case was the correlation coefficient less than 0.95. Equations (12)-(13) are thus a very good analog to the GWLF model. The parameters of interest here are j_{1j} and j_{2j} because they pertain to maize. The OLS estimated values of these parameters were scaled proportionally in order to reproduce estimates of deliveries to surface waters in each watershed based on Nizeyimana et al. (1997). These are the estimates shown in Table 1.

Nitrogen concentration in runoff in the j th watershed is modeled as

$$R_j = q_j \frac{(1-u_j)(N_j/L_j)}{Z_j}, \tag{14}$$

where q_j is a constant scaling factor chosen for each watershed so that, under the current climate and status quo (SQ) scenario, equation (14) reproduces the GWLF estimate of nitrogen concentration in surface runoff for maize (9 milligrams/liter). The term in the numerator, $(1-u_j)(N_j/L_j)$, represents excess nitrogen per hectare. Dividing by Z_j yields a liquid concentration.

Only a portion of deliveries to surface waters in each watershed ultimately reach the Chesapeake Bay, which is the chief area of concern for policy purposes. The proportion of deliveries in the j th watershed that ultimately reach the Bay are modeled as a constant delivery coefficient, w_j, so that total delivered nitrogen loads from maize production to the Bay are

$$S = \sum_j w_j G_j \ . \tag{15}$$

The transport coefficients, which are shown in Table 3, are based on the U.S. Geological Survey's SPARROW (SPAtially Referenced Regressions On Watershed attributes) model (U.S. Geological Survey, 2000).[7]

5. *Climate Scenarios*

We consider three climate scenarios in the model. The first is present-day climate (measured by temperature and precipitation averages for the 1965-1994 period), which serves to establish a reference point. The second climate scenario is based on projections from the Hadley climate model for 2030 (measured by averages for the 2025-2034 period). The Hadley model suggests increases in average daily minimum and maximum temperatures and increases in average annual precipitation (Yarnal, 2000). The third climate scenario is based on projections from the Canadian Climate Centre (CCC) model for 2030 (also measured by averages for the 2025-2034 period). The CCC model suggests a much warmer and drier climate than the Hadley model (Yarnal, 2000). The Hadley and CCC climate model scenarios both include an approximate 22% increase in the atmospheric CO_2 level, from a present-day value of 370 parts per million (ppm) to 450 ppm in 2030 (U.S. National Assessment Synthesis Team, 2000).

In the simulation model, the weather is random in the sense that farmers do not know what temperature and precipitation during the growing season will turn out to be. They must therefore make planting and production decisions on the basis of the distributions of the random temperature and precipitation variables. However, farmers in the model are aware of climate change in the sense that they know how the distributions of these variables are evolving over time in their area. Because the weather is random in the model, the climate scenarios involve changes in the means and variances of the model's temperature and precipitation variables. These variables are assumed to follow a lognormal distribution, which is a reasonable approximation to empirical weather distributions (Teigen and Thomas, 1995).

The changes in the means and variances of the temperature and precipitation variables are set such that the coefficients of variation for these variables stay the same under each climate scenario. In this sense we avoid the issue of whether climate change will lead to changes in climate variability. The impacts that climate change might have on extreme weather events are highly speculative, and indeed the U.S. National Assessment Synthesis Team (2000) has identified this issue as a priority for research. Current climate models do not adequately represent extreme weather events such as floods or heavy downpours. Existing trends for the Chesapeake Bay region suggest a change toward fewer extreme temperatures but more frequent severe thunderstorms and severe winter coastal storms (Yarnal, 2000). Whether these trends will continue is highly uncertain.

There are six weather stations with time series data on precipitation and temperature within the area covered by the twelve watersheds. Each watershed was assigned the weather station closest to it. Means and standard deviations across the twelve watersheds for the temperature and precipitation variables are shown in Table 4. The temperature variable is defined as daily maximum temperature because this is a good indicator of summer heat stress facing maize, which is a concern in a warmer climate.

Climate change is of course a global phenomenon and not confined to the Chesapeake Bay region. A full analysis of climate change impacts on a region must incorporate impacts that arise indirectly due to economic linkages with other regions and countries that are also affected by climate change (Abler et al., 2000). In the present case, changes in climate in other regions and countries could lead to changes in global agricultural supplies and, in turn, agricultural commodity prices facing the Chesapeake Bay region. With this in mind we analyze the case where prices of maize (p) and alternative commodities (p^*) do not change as well as cases where they do change.

Based on the literature review in Schimmelpfennig et al. (1996) and results in McCarl (1999), plausible estimates of commodity prices changes are as follows: (1) for both the Hadley and CCC climate model scenarios, assuming there are CO_2 enrichment effects, a 5% decline in both p and p^*; and (2) for both climate model scenarios, assuming there are no CO_2 enrichment effects, a 5% rise in p and p^*. These price changes are imposed on top of any price changes in a future baseline scenario (see below).

6. Future Baseline Scenarios

We consider two future baseline scenarios in the model. These scenarios describe what might happen to maize production in the Chesapeake Bay region between now and 2030 independent of climate change. Shortle et al. (1999) discuss procedures to use in constructing future baseline scenarios. These procedures do not attempt to predict the future, which is essentially impossible. Instead, they focus on developing scenarios that establish probable upper and lower bounds on economic and environmental impacts. In this way, while one cannot pinpoint the exact magnitude of an impact, one can say that the impact is likely to lie within a certain interval.

With an eye toward establishing probable upper and lower bounds on changes in nitrogen loadings from maize production in the Chesapeake Bay region between now and 2030, we consider two future baseline scenarios. These two scenarios—a continuation of the status quo

(SQ) and an "environmentally friendly," smaller agriculture (EFS)—are described in heuristic terms in Table 5. The EFS scenario is motivated by a number of developments that may occur in Chesapeake Bay region agriculture (Abler and Shortle, 2000). These include rapid improvements in biotechnology, widespread adoption of precision agriculture (which uses remote-sensing and information technologies in order to achieve very precise control over agricultural input applications), a continuation of the historic trend of declining real farm commodity prices, continued conversion of agricultural land to urban uses, and more stringent environmental regulations facing agriculture, which would work to increase nitrogen costs to farmers. Biotechnology and precision agriculture could both significantly increase agricultural productivity, as well as decrease the sensitivity of the region's agriculture to climatic variations (Abler and Shortle, 2000).

Table 2 provides quantitative details on differences in the model's parameters between the SQ and EFS scenarios. To manifest the productivity-enhancing impacts of biotechnology and precision agriculture, levels of capital-augmenting technical change (A_K), labor-augmenting technical change (A_N), and fertilizer-augmenting technical change (A_F) are 60% greater in the EFS scenario than in the SQ scenario, while the level of land-augmenting technical change (A_L) is 100% greater. The share of fertilizer in the biological production function (b) in the EFS scenario is only one-half of its share in the SQ scenario, reflecting a shift toward more "environmentally friendly" production techniques. The elasticity capturing the impact of atmospheric CO_2 on climate productivity (f) increases from 0.8 to 0.9, reflecting changes in crop breeding to take better advantage of high CO_2 levels. Output prices for maize (p) and alternative commodities (p^*) in the EFS scenario are about two-thirds of their values in the SQ scenario, reflecting continued declines in global real agricultural commodity prices. The fertilizer price (p_F) is 20% greater in the EFS scenario than in the SQ scenario, reflecting the impacts of stricter environmental regulations on nitrogen costs to farmers. Several elasticities in the climate productivity equation (10) are lower in absolute value in the EFS scenario than in the SQ scenario, reflecting a decrease in climate sensitivity on the part of the region's agriculture. The land supply shifter (z) is significantly lower in the EFS scenario than in the SQ scenario, reflecting continued conversion of agricultural land to urban uses and some abandonment of marginal agricultural land.[8]

The EFS scenario is much more probable than any scenario approximating a continuation of the status quo, but both scenarios are needed to establish probable bounds on climate change impacts. The EFS scenario establishes a lower bound on any increase in nitrogen loadings due to climate change because biotechnology and precision agriculture help minimize loadings from any given level of agricultural production. In addition, stricter environmental regulations in the EFS scenario lead farmers to adopt less nitrogen-intensive maize production practices. None of these things occur in the SQ scenario, and so the SQ scenario establishes an upper bound on increases in nitrogen loadings due to climate change. One should not interpret the EFS scenario as our "prediction" of the future.

With three climate scenarios and two future baseline scenarios, there are a total of six ($3\times2 = 6$) scenario combinations to be analyzed. Because the weather is random, we analyzed each combination using a Monte Carlo experiment in which we took 1,000,000 random samples of the model's temperature and precipitation variables.[9] For a given set of production decisions by farmers, each of the Monte Carlo random samples can be thought of as an alternative possible outcome of those decisions.

7. Simulation Model Results

Results from the simulation model for total nitrogen deliveries from maize production to the Chesapeake Bay are presented in Table 6. Results for the amount of land allocated to maize are shown in Table 7, while results for nitrogen applications per hectare of maize are shown in Table 8. Results for maize yields are presented in Table 9.[10] Tables 6 and 9 report means and standard deviations over the 1,000,000 random samples. The results in Tables 7 and 8 are the same for all random samples because land allocations and fertilizer applications are nonstochastic—they are chosen by farmers at the start of the growing season on the basis of expected weather rather than actual weather.

As noted above, we report results both for the case with CO_2 enrichment effects and the case without them; as well as for the case where agricultural commodity prices change due to the effects of climate change on global agricultural markets and the case where prices do not change. In addition, because the literature to date on climate change and water quality has not considered economic responses by farmers, for comparison purposes we report results under the case where farmers respond according to the economic model above and the case where farmers do not respond at all. In the case where farmers do not respond, the amount of land allocated to maize and nitrogen applications per hectare of maize are both fixed at their values under the present-day climate.[11] In this case, because land allocations and nitrogen applications are fixed, nitrogen loadings are the same regardless of whether or not agricultural commodity prices change.

Begin with the case where farmers respond to climate change, there are CO_2 enrichment effects, and agricultural commodity prices do not change. Under the SQ baseline scenario, both the Hadley and CCC climate models suggest that nitrogen deliveries to the Chesapeake Bay would increase. The Hadley model indicates that the mean value of deliveries would increase from 3186 mt to 3609 mt (13% rise),[12] while the CCC model indicates that mean deliveries would increase to 3206 mt (1% rise). It may seem surprising that deliveries should increase in the CCC model, given that mean values for the precipitation variables decline (see Table 4). Furthermore, in both the Hadley and CCC models, increases in atmospheric CO_2 lead to increases in nitrogen uptake by maize; the mean value of climate productivity (u_j) across the twelve watersheds rises from 0.7 to 0.74 in the Hadley model and 0.72 in the CC model. Other things equal, an increase in uptake reduces runoff simply because less nitrogen is available to run off. However, the increase in uptake also makes maize production in the region more economically attractive. As a result, both the amount of land allocated to maize (Table 7) and the amount of nitrogen applied per hectare of maize (Table 8) increase. This causes nitrogen deliveries to increase, even in the CCC model.

Continue with the case where farmers respond to climate change, there are CO_2 enrichment effects, and agricultural commodity prices do not change. The Hadley and CCC models are split in this case regarding the direction of change in nitrogen deliveries under the EFS baseline scenario. The Hadley model indicates that the mean value of deliveries would increase from 974 mt to 1039 mt (7% rise), while the CCC model indicates that mean deliveries would decrease to 947 mt (3% fall). Like the SQ baseline scenario, farmers respond to increases in atmospheric CO_2 in the EFS baseline scenario by increasing the land allocated to maize and nitrogen applications per hectare. However, in the EFS/CCC model scenario, decreases in precipitation and increases in nitrogen uptake are together sufficient to cause nitrogen deliveries to decline in spite of economic responses by farmers.

Now consider the case where farmers respond to climate change, there are CO_2 enrichment effects, and agricultural commodity prices change. Commodity prices fall modestly in this case because the CO_2 enrichment effect, combined with changes in temperature and precipitation, benefits worldwide agricultural production of maize and alternative crops. In this case, nitrogen deliveries to the Chesapeake Bay decrease significantly in both the Hadley and CCC climate models under both the SQ and EFS baseline scenarios. In the SQ scenario, the Hadley model indicates that the mean value of deliveries would decrease from 3186 mt to 2405 mt (25% fall), while the CCC model indicates that they would decrease to 2138 mt (33% fall). In the EFS scenario, the Hadley model indicates that the mean value of deliveries would decrease from 974 mt to 805 mt (17% fall), while the CCC model indicates that they would decrease to 735 mt (25% fall). These decreases in deliveries are due largely to the fact that commodity price declines make maize production in the Chesapeake Bay region less economically attractive. The Chesapeake Bay region is an economically marginal producer of maize relative to other regions such as the U.S. Corn Belt—even modest price declines are sufficient to cause Chesapeake Bay farmers to cut back on maize acreage and significantly reduce nitrogen applications per hectare of maize.[13]

The flip side of these results can be found in the case where farmers respond to climate change and agricultural commodity prices change but there are no CO_2 enrichment effects. Commodity prices rise modestly in this case because the absence of CO_2 enrichment effects makes climate change unfavorable to worldwide agricultural production of maize and alternative crops. In this case, nitrogen deliveries to the Chesapeake Bay increase significantly. In the SQ scenario, the Hadley model indicates that the mean value of deliveries would increase from 3186 mt to 5004 mt (57% rise), while the CCC model indicates that they would increase to 4381 mt (38% rise). In the EFS scenario, the Hadley model indicates that the mean value of deliveries would increase from 974 mt to 1322 mt (36% rise), while the CCC model indicates that they would increase to 1194 mt (23% rise). These increases in deliveries are due largely to the fact that commodity price increases make maize production in the Chesapeake Bay region more economically attractive, leading to additional maize acreage and higher nitrogen applications per hectare.

The results for the cases where farmers respond to climate change differ significantly from the corresponding cases where farmers do not respond. For example, consider Hadley model results for the SQ baseline scenario in the case where there are CO_2 enrichment effects. If farmers do not respond to climate change, there is a decline in nitrogen deliveries from 3186 mt to 2962 mt (7% decrease). On the other hand, if farmers do respond, there is a decline in nitrogen deliveries to 2405 mt when commodity prices change (25% decrease) and a rise in deliveries to 3609 mt when commodity prices do not change (13% increase). Regardless of whether or not commodity prices change, the no-response result misses the mark by over 550 mt (17%). Furthermore, when commodity prices do not change, the no-response result is incorrect regarding the direction of change in nitrogen deliveries. Similar discrepancies occur with the CCC model and in the EFS baseline scenario.

The results for the SQ and EFS baseline scenarios differ significantly from each other in part because the EFS scenario starts from a much lower level than the SQ scenario. Under the present-day climate, mean deliveries to the Chesapeake Bay are only 974 mt in the EFS scenario, compared to 3186 mt in the SQ scenario. The difference between these two figures (2212 mt) is larger than the largest climate change impact in all the scenarios and cases considered. There are many forces at work that cause nitrogen deliveries to be much lower in the EFS scenario than in the SQ scenario. As noted above, biotechnology and precision agriculture help minimize nitrogen loadings from any given level of agricultural production. In addition, stricter environmental regulations in the EFS scenario lead farmers to adopt less nitrogen-intensive maize production practices. The results for the SQ and EFS scenarios also differ because agriculture is less climate-sensitive in the EFS scenario than in the SQ scenario.

The results in Table 6 also help illustrate the potential effects of climate change on the variability in nitrogen deliveries to the Chesapeake Bay. Variability is important if the economic or ecological damages caused by nitrogen deliveries are a nonlinear function of total deliveries (e.g., because of threshold effects in damages). For example, the economic costs of pollution are often modeled as an increasing, convex function of the ambient level or concentration of a pollutant. In this case, less variability is preferred to more variability, other things equal. The results in Table 6 indicate that the standard deviation in nitrogen deliveries moves largely in tandem with mean deliveries—when mean deliveries change, the standard deviation changes in the same direction and by a similar percentage amount. As a caveat, the ability of the model to shed light on variability in nitrogen deliveries is limited by our assumption that the coefficients of variation for the precipitation and temperature variables are the same under each climate scenario.

The results for maize yields in Table 9 within a particular baseline scenario (SQ or EFS) can be explained in large part by the changes in nitrogen applications per hectare of maize shown in Table 8. When nitrogen applications change, the mean value of the maize yield changes in the same direction. Of course, changes in climate have independent impacts on maize yields above and beyond impacts occurring indirectly through changes in nitrogen application decisions by farmers, so that the results in Tables 8 and 9 do not parallel each other exactly. The changes in technology and environmental policy toward agriculture that are part of the EFS scenario cause nitrogen applications per hectare to be significantly lower in the EFS scenario than in the SQ scenario. These technological changes, however, also cause maize yields to be significantly higher in the EFS scenario than in the SQ scenario.

8. Conclusions

Four main conclusions emerge from our results. First, economic responses by farmers to climate change do matter, in the sense that they have major impacts on environmental externalities due to climate change. As our results indicate, assuming that farmers do not respond to changes in temperature, precipitation, and particularly atmospheric CO_2 levels could lead to mistaken conclusions about the magnitudes and even the directions of environmental impacts. While our research is limited to water pollution from agriculture, this result has broader implications for research on the impacts of climate change on environmental quality: the indirect impacts of climate-economy interactions may well be of as much importance to the environmental impacts of climate change as direct climate-environment interactions. The flip side of this result is that the market impacts of climate change in these sectors (changes in output, prices, producer and consumer welfare) may provide a very limited picture of the overall consequences of climate-induced change in sectors with significant nonmarket impacts (e.g., agriculture, forests, energy).

Second, environmental impacts are highly dependent on the climate and future baseline scenarios used. Our simulation results indicate that changes in nitrogen deliveries from maize production to the Chesapeake Bay differ significantly depending on whether we use our status quo (SQ) baseline scenario or our environmentally friendly, smaller agriculture (EFS) baseline scenario. In fact, the difference in nitrogen deliveries between the SQ and EFS scenarios under the present-day climate is larger than the largest climate change impact in all of the scenarios and cases considered. Our results also indicate that changes in nitrogen deliveries differ depending on whether we use projections from the Hadley climate model or the Canadian Climate Centre (CCC) model.

Third, environmental impacts are also highly on the effects of climate change on agriculture in other regions and countries, which are in turn dependent on the ability of maize to productively use higher atmospheric levels of carbon dioxide (CO_2). CO_2 enrichment effects could lead to an expansion in global production of maize and many other crops, causing global agricultural commodity prices to fall. As an economically marginal producer of maize, the Chesapeake Bay region is sensitive to changes in the price of maize.

Finally, additional research is needed on extreme weather events. Current climate models do not adequately represent extreme weather events such as floods or heavy downpours, which can wash large amounts of fertilizers, pesticides, and animal manure into surface waters. For this reason, we did not incorporate extreme weather events into our model. However, changes in extreme events could overwhelm the environmental effects of changes in average levels of precipitation or temperature as well as the effects of changing atmospheric CO_2 levels.

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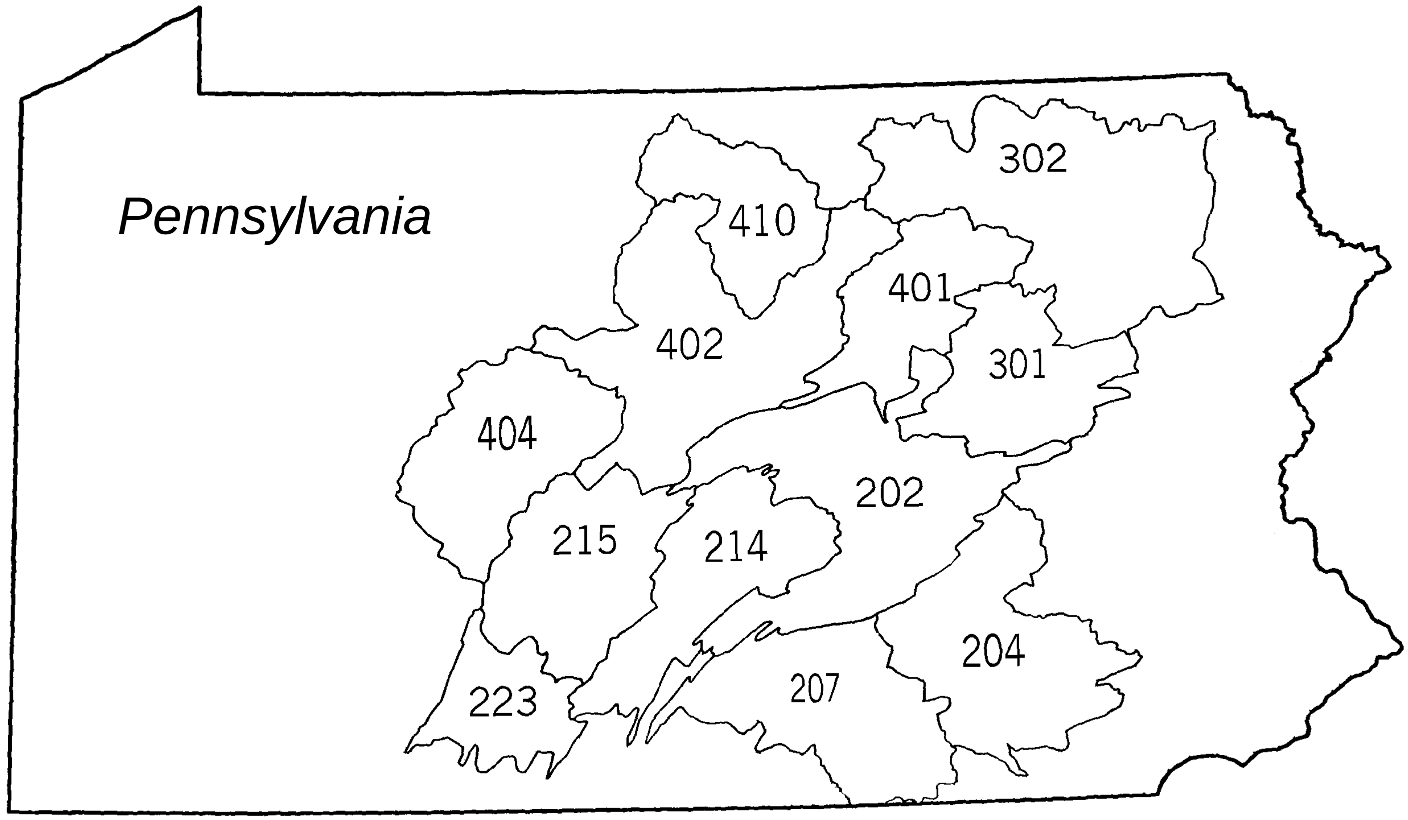

Figure 1. Study Watersheds in the Chesapeake Bay Region

Table 1. Land Area, Maize Production, and Nonpoint Loadings in the Twelve Study Watersheds

Watershed	Land Area (1000 ha)		Maize Yield (mt/ha)	Number of Farms Growing Maize	Nitrogen Applied to Maize (kg/ha)	Nonpoint Loadings from Maize Delivered to Surface Waters		Nonpoint Loadings from Maize Reaching Chesapeake Bay (mt)
	Total	Maize				Rate (kg/ha)	Total Load (mt)	
202	571.9	32.3	6.83	1531	157	24	761	540
204	440.6	53.3	8.14	3049	187	26	1396	1021
207	395.1	35.6	6.02	1322	138	25	886	515
214	330.6	13.1	7.16	906	165	23	303	207
215	347.1	8.8	6.72	415	155	23	203	127
223	186.2	4.6	6.16	254	142	23	105	30
301	299.7	12.9	6.40	504	147	28	362	246
302	668.0	8.2	6.47	398	149	27	219	134
401	267.6	12.7	6.93	484	159	25	323	208
402	594.3	10.5	6.57	500	151	18	191	107
404	360.8	3.6	5.74	274	132	18	66	33
410	245.5	1.6	7.03	89	162	18	29	16
Total or Average	4707.4	197.2	6.97	9726	160	25	4845	3185

NOTE: A total may not equal the sum over the watersheds because of rounding.

Table 2. Economic Model Parameters

Model Parameter	Value in Status Quo (SQ) Scenario	Value in Environmentally Friendly, Smaller Agriculture (EFS) Scenario
Productivity Parameters		
Capital productivity (A_K)	1	1.6
Labor productivity (A_N)	1	1.6
Fertilizer productivity (A_F)	1	1.6
Land productivity (A_L)	1	2
Elasticities of Substitution		
Upper-level production function (s)	0.3	0.3
Mechanical production function (h)	0.8	0.8
Biological production function (b)	0.5	0.5
Factor Proportions		
Mechanical share in upper-level production function (a)	0.75	0.75
Capital share in mechanical production function (m)	0.7	0.7
Fertilizer share in biological production function (b)	0.4	0.2
Land's share, alternative commodities (s^*)	0.2	0.25
Output and Input Prices		
Maize output price (p)	1	0.65
Price of alternative commodities (p^*)	1	0.65
Fertilizer price (p_F)	1	1.2
Rental rate on capital (p_K)	1	1
Wage rate (p_N) (numeraire)	1	1
Climate Productivity Parameters		
Elasticity with respect to atmospheric CO_2 level (f)	0.8	0.9
Elasticity with respect to mean precipitation, period 2 (a_2)	0.3	0.3
Elasticity with respect to deviation of precipitation from mean, period 1 (e_1)	0.6	0.4

Model Parameter	Value in Status Quo (SQ) Scenario	Value in Environmentally Friendly, Smaller Agriculture (EFS) Scenario
Elasticity with respect to deviation of precipitation from mean, period 2 (e_2)	1	0.7
Elasticity with respect to mean temperature, period 2 (m_2)	-0.3	-0.2
Elasticity with respect to deviation of temperature from mean, period 2 (d_2)	-8	-6
Land Supply		
Land supply shifter (z)	1	0.30
Elasticity with respect to rental rate on maize land (g)	0.5	0.5
Elasticity with respect to rental rate on land for other commodities (x)	-0.4	-0.4
Maize Production		
Elasticity with respect to ratio of actual to expected climate productivity (l)	3.8	3.8

Table 3. SPARROW Model Parameters

Watershed	Parameter Value (w_j)
202	0.710
204	0.731
207	0.581
214	0.684
215	0.626
223	0.287
301	0.681
302	0.611
401	0.643
402	0.560
404	0.500
410	0.565

Table 4. Means and Standard Deviations of Weather Variables (all 12 watersheds)

Variable	Present-Day Climate	Hadley Climate Model	CCC Climate Model
Precipitation, Time Period 1 (Z_1) (millimeters)	279 (39)	305 (43)	276 (39)
Precipitation, Time Period 2 (Z_2) (millimeters)	288 (46)	315 (51)	285 (46)
Precipitation, Time Period 3 (Z_3) (millimeters)	315 (44)	345 (48)	312 (44)
$Z = Z_1 + Z_2 + Z_3$ (millimeters)	882 (75)	965 (82)	873 (74)
Average Daily Maximum Temperature, Time Period 2 (T_2) (Celsius)	26.9 (0.5)	28.2 (0.5)	29.1 (0.5)

NOTE: Means are opposite variables names; standard deviations are in parentheses. These are weighted means and standard deviations across the twelve watersheds, where the weight for a watershed is defined as its share of total maize production in the twelve watersheds.

Table 5. Future Baseline Scenarios for the Year 2030

Scenario	Scenario Description
"Environmentally Friendly," Smaller Agriculture (EFS)	• Significant decrease in number of commercial maize farms in Chesapeake Bay region • Substantial increase in agricultural productivity due to biotechnology and precision agriculture • Major increase in maize production per farm and maize yields on remaining commercial farms • Significant decrease in agriculture's sensitivity to climate variability due to biotechnology and precision agriculture • Continued conversion of agricultural land to urban uses, with some abandonment of unprofitable agricultural land • Significant decrease in commercial fertilizer and pesticide usage due to biotechnology • Less runoff and leaching of agricultural nutrients and pesticides due to precision agriculture • Stricter environmental regulations facing agriculture
Status Quo (SQ)	Agriculture as it exists today in the Chesapeake Bay region

Table 6. Nonpoint Nitrogen Loadings from Maize Delivered to the Chesapeake Bay (all 12 watersheds; in metric tons)

Do Farmers Respond to Climate Change?	Are There CO_2 Enrichment Effects?	Do Agricultural Commodity Prices Change?	Status Quo (SQ) Scenario			Environmentally Friendly, Smaller Agriculture (EFS) Scenario		
			Present-Day Climate	Hadley Climate Model	CCC Climate Model	Present-Day Climate	Hadley Climate Model	CCC Climate Model
Yes	Yes	No	3186 (456)	3609 (558)	3206 (476)	974 (99)	1039 (112)	947 (99)
Yes	Yes	Yes	3186 (456)	2405 (358)	2138 (306)	974 (99)	805 (85)	735 (76)
Yes	No	No	3186 (456)	3569 (528)	3128 (444)	974 (99)	1067 (111)	964 (98)
Yes	No	Yes	3186 (456)	5004 (771)	4381 (644)	974 (99)	1322 (139)	1194 (123)
No	Yes	No/Yes	3186 (456)	2962 (451)	2862 (421)	974 (99)	899 (96)	858 (90)
No	No	No/Yes	3186 (456)	3354 (494)	3229 (460)	974 (99)	1030 (107)	980 (99)

NOTE: The figures shown for each scenario are means and standard deviations (in parentheses) across 1,000,000 random samples. The mean for the SQ scenario and present-day climate (3186) is a sample mean and, as such, does not need to agree exactly with the figure in Table 1 (3185).

Table 7. Land Allocated to Maize
(all 12 watersheds; in thousands of hectares)

Do Farmers Respond to Climate Change?	Are There CO_2 Enrichment Effects?	Do Agricultural Commodity Prices Change?	Status Quo (SQ) Scenario			Environmentally Friendly, Smaller Agriculture (EFS) Scenario		
			Present-Day Climate	Hadley Climate Model	CCC Climate Model	Present-Day Climate	Hadley Climate Model	CCC Climate Model
Yes	Yes	No	197	212	205	144	152	149
Yes	Yes	Yes	197	195	190	144	145	143
Yes	No	No	197	202	195	144	146	143
Yes	No	Yes	197	213	206	144	150	147
No	Yes	No/Yes	197	197	197	144	144	144
No	No	No/Yes	197	197	197	144	144	144

Table 8. Nitrogen Applications per Hectare of Maize (all 12 watersheds; in kilograms)

			Status Quo (SQ) Scenario			Environmentally Friendly, Smaller Agriculture (EFS) Scenario		
Do Farmers Respond to Climate Change?	**Are There CO_2 Enrichment Effects?**	**Do Agricultural Commodity Prices Change?**	**Present-Day Climate**	**Hadley Climate Model**	**CCC Climate Model**	**Present-Day Climate**	**Hadley Climate Model**	**CCC Climate Model**
Yes	Yes	No	160	179	171	74	81	79
Yes	Yes	Yes	160	134	128	74	66	64
Yes	No	No	160	166	157	74	76	74
Yes	No	Yes	160	212	201	74	90	87
No	Yes	No/Yes	160	160	160	74	74	74
No	No	No/Yes	160	160	160	74	74	74

Table 9. Maize Yields
(all 12 watersheds; in metric tons per hectare)

			Status Quo (SQ) Scenario			Environmentally Friendly, Smaller Agriculture (EFS) Scenario		
Do Farmers Respond to Climate Change?	**Are There CO_2 Enrichment Effects?**	**Do Agricultural Commodity Prices Change?**	**Present-Day Climate**	**Hadley Climate Model**	**CCC Climate Model**	**Present-Day Climate**	**Hadley Climate Model**	**CCC Climate Model**
Yes	Yes	No	6.97 (1.43)	7.74 (1.37)	7.40 (1.40)	10.49 (1.61)	11.47 (1.50)	11.16 (1.54)
Yes	Yes	Yes	6.97 (1.43)	6.56 (1.16)	6.26 (1.18)	10.49 (1.61)	10.54 (1.38)	10.25 (1.41)
Yes	No	No	6.97 (1.43)	7.20 (1.42)	6.85 (1.44)	10.49 (1.61)	10.72 (1.59)	10.39 (1.62)
Yes	No	Yes	6.97 (1.43)	8.25 (1.62)	7.87 (1.65)	10.49 (1.61)	11.51 (1.70)	11.16 (1.74)

NOTE: The figures shown for each scenario are means and standard deviations (in parentheses) across 1,000,000 random samples. The model does not calculate yields under the case where farmers do not respond to climate change.

Endnotes

[1] The expected cost function C_j^e emerges as a solution to the problem of minimizing total input expenditures subject to the constraint that the expected level of output be greater than or equal to Y_j^e (Just, 2000). The actual level of output (Y_j) is stochastic because climate productivity (u_j) is stochastic. In general, C_j^e would depend not only on the expected level of climate productivity (u_j^e) but also on the higher-order moments of u_j. However, there is little evidence on how the higher-order moments should enter into the expected cost function. It may be noted that u_j^e depends on both the means and variances of the model's temperature and precipitation variables, so that the higher-order moments of those variables do affect C_j^e.

[2] The approximation is exact if the expected cost function for alternative commodities is Cobb-Douglas.

[3] The formulation for climate productivity is not invariant with respect to the units of measurement for temperature. A change in units of measurement (for example, from Celsius to Fahrenheit) would have to be accompanied by changes in the elasticities m_i and d_i to leave the impact of a change in the temperature on climate productivity approximately unchanged.

[4] The equation $\ln y_t = u_0 + u_1 t$, where y_t is maize yield and t is the year, was estimated by ordinary least squares (OLS) using Pennsylvania data for 1950-2000, and used to calculate predicted yields $\hat{y}_t$. We then calculated the coefficient of variation of the detrended yield variable $\left(y_t - \hat{y}_t\right)$.

[5] For the time series case, we ran OLS regressions of the log of Pennsylvania maize yield on time and on temperature and precipitation variables for our four time periods, using 1950-1994 weather data in Teigen and Thomas (1995). These regressions were used to infer values of the elasticities e_i and d_i. For the cross-sectional case, we ran OLS regressions of the log of maize yield for 41 U.S. states on means of the temperature and precipitation variables for the 1950-1994, again using data from Teigen and Thomas (1995). We also included as control variables the fraction of maize acreage irrigated in a state as well as dummies for the Mid-Atlantic, Corn Belt, and Pacific regions. Cross-sectional regressions such as this capture longer-term adjustments to differences in climate and other growing conditions (Kislev and Peterson, 1982). We thus used these regression results to infer values for the elasticities a_i and m_i.

[6] In watershed 302, the results when the term $\left(Z_j^2 R_j\right)^2 L_j$ were included were unsatisfactory. We therefore dropped this term for that watershed.

[7] Climate change could lead to changes in stream/river flow that might affect pollutant transport (Chang et al., 1999). The GWLF model takes into account changes in stream/river flow within a watershed but not changes in flow between the boundary of a watershed and the Chesapeake Bay. However, we lack evidence on how any changes in flow might influence the SPARROW model coefficients.

[8] The value of z in the EFS scenario is set so that, taking into account changes in the rental rate on land for alternative commodities, the supply curve for land is shifted inward by 40% relative to the SQ scenario.

[9] The procedure used here for choosing the sample size of a Monte Carlo experiment is described in Abler et al. (1999). We apply this procedure here with the objective of limiting the margin of error in the estimated mean value of deliveries of nitrogen from maize to the Chesapeake Bay (S). A sample size of 1,000,000 can be shown to be sufficient to achieve, with a 99% probability, an upper limit of 0.1% on the margin of error in the estimated mean value of S in each scenario.

[10] Yields are based on the approximation to production in equation (11). This approximation is in turn based on observed economic responses by farmers during the 1950-2000 period. As such, the model does not calculate yields in the case where farmers do not respond to climate change.

[11] For the status quo (SQ) scenario, these values are simply the figures reported in Table 1. For the environmentally friendly, smaller agriculture (EFS) scenario, these values represent the solution to the model given the present-day climate and EFS scenario.

[12] This change and all the other changes in means that are discussed in the text are statistically significant at the 1% level.

[13] Demands within the region for maize (for dairy and poultry operations, etc.) could be met in this case through purchased feed supplied by other regions.