OCEAN THERMAL LAG AND COMPARATIVE DYNAMICS OF DAMAGE TO AGRICULTURE FROM GLOBAL WARMING

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ABSTRACT

As CO_2 equivalent gases increase beyond a doubling, there will likely be unavoidable damage to U.S. agriculture. In equatorial regions of the world, damage from global warming will occur earlier than in the U.S. Biogeophysical lags, including deep-ocean mixing with warmer surface waters, can delay the warming caused by CO_2 emissions. In this chapter, comparative dynamics trace the path of damage to U.S. agriculture from climate change, after considering adaptation to climate change, technological change that will occur both with and without climate change, and ocean thermal lag.

INTRODUCTION

In order to understand the effect of human activity on climate, we cannot perform controlled experiments. A useful alternative is to perform a thought experiment to answer the question, "what would happen to the earth's climate if a pulse of greenhouse gases were injected into the atmosphere, doubling the concentration of those gases emitted by human activity, especially economic

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production and consumption?" That type of computer modeling exercise is familiar to economists as an example of comparative statics. Most of the modeling done by climate experts is based on the idea of a doubling of anthropogenic greenhouse gases. Economists have borrowed the physical science models, as well as the limitations of those models. For example, the model by Nordhaus (1994) relies on a model of climate change that may be a reasonable approximation for a doubling, but not reasonable for a tripling or quadrupling, as discussed in detail in the next section.

A comparative statics approach to the economic benefits and costs of global warming and policies to slow it can lead to faulty analysis. One comparative static analysis of the damage from a rising sea-level found a very low cost. In the new equilibrium, while the former coast will be submerged, new valuable coastal property will be available so the author valued loss using less valuable interior land (Nordhaus, 1993). To avoid that type of error, Nordhaus (1994) calculates the time path of the impact of climate. But if the climate model used by Nordhaus is not applicable to increases in greenhouse gases beyond a doubling, what is the potential that the arbitrary selection of the terminal time affects the results? Economists argue that future benefits and costs beyond 50 to 100 years will not greatly affect the analysis of benefits and costs of policy today. One reason is the discount rate used to convert future dollars into present dollars. Another reason is that policy can be adjusted over time as we learn more about the effects of climate change. Consider these two reasons in turn.

For a population that is stable over time, the social rate of time preference is the sum of two parts. One part is the pure rate of time preference to consume today rather than in the future. The second part depends on whether or not the economy is growing, and weights the value of consumption depending whether future generations have relatively more or less to consume. Economists disagree over the values that should be placed on each part separately and jointly. Arrow et al. (1996) present the arguments between two approaches. Khanna and Chapman (1996) derive the equation that underlies the debate, and review the fundamental issues, economic efficiency and intergenerational equity. Howarth and Norgaard (1995) argue that discounting based solely on efficiency can lead to policy inaction that leaves future generations worse off than the present, and argue for policies that directly account for intergenerational transfers of wealth and poverty through damage to the environment.

Among economic analyses of climate change, discount rates differ significantly. Nordhaus (1994) suggests using a rate of social time preference equal to 3% to discount consumption. His corresponding discount rate for capital investments required by policy starts at 6% and falls over time to 3% as economic growth slows, roughly equivalent to a constant, annual discount rate of 4.6% (Nordhaus, 1994, p.131). Cline (1992, p.255) argues that intergenerational discounting is indefensible, and recommends a social rate of time preference for consumption equal to 1.5%.

In a previous paper (Hall, 1999), I analyze two climate scenarios that eventually damage between one-third and two-thirds of U.S. agricultural consumer and producer surplus. A third climate scenario leads to eventual collapse of agriculture. I then compare two discount rates, 5% and 1% (Hall, 1999, Fig. 10, p. 207). With a discount rate of 5%, the present value of the impact on economic surplus from climate change is slightly positive or equal to zero in the three climate scenarios, because of slight gains in the early years as climate warms. In one case, the damage begins at year 2025, yet with a discount rate of 5% there is no value to avoid damage that occurs later. With a discount rate of 1%, the result is that for all three climate scenarios there is substantial damage that justifies equally large payments for policies that would avoid climate change. Just splitting the difference, a 3% discount rate gives results virtually indistinguishable from a 5% discount rate. The reason is that for a 5% discount rate the first 100 years of analysis determine 80% of the present value, compared to a 1% discount rate where the present value depends on when the analysis ends. Consequently, the argument is unreasonable that social discounting justifies an end to economic analysis at a doubling of greenhouse gases.

The question in this chapter is whether policy can be adjusted over time as we learn more about the effects of climate change, and still avoid potentially disastrous outcomes. While the definitive answer to this question requires more analysis than can be developed here, this study presents the case that there is no *a priori* reason to dismiss the question. There are several components essential to this analysis. First is a clear consideration of the amount of economically available fossil fuels. This point should be obvious. Work by most economists, however, either just considers a doubling of greenhouse gases, selects an arbitrary time frame, or obscures this consideration among myriad assumptions about autonomous increases in energy efficiency or endogenous improvements in renewable and alternative energy technology without justification or concomitant improvements in fossil fuel technology. Second is a climate model that can analyze emissions of greenhouse gases beyond a doubling. Third is a dynamic representation of the impacts of global warming and associated climate change on an important sector of the economy. The remaining portion of this introduction summarizes these components.

The terminology “demonstrated recoverable reserves” refers to the amounts measured and indicated that can be extracted at today’s prices and with today’s

Table 1. Recoverable Reserves.

	EIA (1995)		Edmunds & Reilly (1985)	
Identified Coal[a]	1,145,000[d] mst	WEC (1992)	693,270[g] mmtce	WEC (1980)
Demonstrated Oil[b]	1,000[e] bbl	Oil&GasJ (1993)	610[h] bbo	Oil&GasJ (1980)
Demonstrated Gas[c]	5,000[f] tcf	Oil&GasJ (1993)	2,670.403[i] tcf	Oil&GasJ (1980)

[a] Identified = demonstrated and inferred.
[b] Demonstrated = measured and indicated.
[c] Demonstrated = measured and indicated.
[d] mst = million short tons, table 11.16, p. 315.
[e] bbl = barrels, rounded from table 11.3, p. 289.
[f] tcf = trillion cubic feet, rounded from table 11.3, p. 289.
[g] mmtce = million metric tons of coal equivalent, table 11–2, p. 156.
[h] bbo = billions of barrrels of oil, Oil and Gas Journal estimates adjusted by Edmunds and Reilly, table 7–4, p. 81.
[i] tcf = trillion cubic feet, table 9–3, p. 122.

technology. "Reserves" also includes amounts inferred from existing deposits, extractable at today's prices and with existing technology. Over time, new discoveries, changing prices, and changes in technology have increased recoverable reserves (Table 1). As fossil fuels are used up, prices will rise, adding reserves. Over time, we expect that technology will continue to improve the fraction that is recoverable. We will also discover deposits that are now considered hypothetical and speculative. As prices rise, there will be substitution among fossil fuels, taking into account costs to convert among solid, liquid, and gaseous forms, and the uses of those forms for heating, transportation, and electricity. Eventually, fossil fuel prices will rise to the point where alternative energy sources make fossil fuels uneconomic. Edmonds and Reilly (1985) estimate "recoverable resources," which they define to include identified and undiscovered deposits that will be recoverable with future technology at future prices, accounting for substitution among fossil fuels.

Edmonds and Reilly (1985) survey the literature on estimates of recoverable resources for all forms of fossil fuels and recovery technologies. While their review is dated, it remains the only summary that adjusts the estimates to make them consistent across fossil fuels and definitions (including undiscovered – hypothetical in known districts and speculative). Of all the sources, shale oil is both the largest resource and the resource for which the least is known about the range of values that will become economic. Heavily discounting their estimate for shale oil, Table 2 reproduces their estimates, and with the

Table 2. Long Term Economic Resources and Cumulative CO_2 Emissions: Maximum Coal Price at $85/metric-ton.

	Recoverable resources (exajoules)			Maximum Cumulative Emissions (metric gigatons carbon)		
	Low	Best	High	Low	Best	High
Coal	146500[a]	330000	527400[a]	3567.774	8036.625	12843.99
Oil-conventional	44600	13400	15200[b]	815.7981	245.1053	278.0299
Enhanced oil recovery	1500	3500[c]	5500	27.43716	64.02003	100.6029
Tar sands	700	4100[c]	7500	12.80401	74.9949	137.1858
Shale	4400[d]	6100[d]	91800[d]	80.48233	111.5778	1679.154
Gas-conventional	6300	11400	13500	84.94966	153.7184	182.035
Gas in tar sands	40[e]	320[c]	600[e]	0.539363	4.314903	8.090444
Gas in coal seams	30[e]	40[c]	50[e]	0.404522	0.539363	0.674204
Gas in shale	30[e]	40[c]	50[e]	0.404522	0.539363	0.674204
Total	204100	368900	661600	4590.594	8691.435	15230.43

Source: Edmonds and Reilly (1985), Table 1-3, p. 8, unless otherwise indicated.
Prices (1979$) up to: $10/mcf – gas; $40/bbl – oil; $85/metric-ton – U.S. coal.
mcf = thousand cubic feet bbl = barrels
[a] Converted (multiply by 29.3, round) from p. 160, "5,000 to 18,000 GT of coal are available for exploitation at costs less than $85/ton (1979 dollars)."
[b] Equals best estimate plus Δ, where Δ = best – low.
[c] Average of high and low estimates.
[d] Converted (multiply by 5.8 × 1.055056, round) from Table 8-3, p. 98. Resource Grade: 25 to 100 gallons of oil per ton of shale. Low: Measured and indicated; Best: measured, indicated and inferred; High: identified and undiscovered.
[e] Converted (multiply by 1.055056, round) from Table 10-3, p. 146.

exceptions noted in the table the values correspond to those given in Edmonds and Reilly (1985, Tables 1–3, p. 8).

Given the numbers in Table 2, the ultimate fossil fuel to provide energy in solid, liquid, and gaseous forms is coal. Edmonds and Reilly (1985) estimate that global economically available coal equals between 5,000 and 18,000 metric Gigatons (Gt), at an eventual price of $85/metric-ton (1979 prices). Cline (1992) adjusts upward their estimate for coal to the range of 10,000 and 20,000 Gt. Cline's adjustment is to account for the estimate by Manne and Richels (1990) that the cost of the backstop technology for fossil fuels would require a tax of $250 per metric ton of carbon emissions from coal (1988 prices). Deflating to 1979 dollars, Cline calculates the price of coal equal to $118 per metric ton of coal, at which coal eventually becomes uneconomic.

Table 3 replaces the coal estimates by Edmonds and Reilly with those of Cline.

Cline converts tons of coal to tons of carbon emissions from coal, and he cites Nordhaus and Yohe (1983) for the conversion factor. Based on the emission rates given in Table 4, Table 3 shows that the maximum cumulative emissions from coal vary between 7 and 14 metric teratons, the amounts Cline uses for his analysis. Accounting for all fossil fuels, Table 3 presents a range that varies between 8 and 17 metric teratons. Thus, the world's economically available fossil fuels contain between some 8 and 17 metric teratons of carbon. The rate of emissions over time is based upon three macro-economic models

Table 3. Long Term Economic Resources and Cumulative CO_2 Emissions: Maximum Coal Price at \$118/metric-ton.

	Recoverable resources (exajoules)			Maximum Cumulative Emissions (metric gigatons carbon)		
	Low	Best	High	Low	Best	High
Coal	293000[a]	439500	586000[a]	7135.549	10703.32	14271.1
Oil-conventional	44600	13400	15200[b]	815.7981	245.1053	278.0299
Enhanced oil recovery	1500	3500[c]	5500	27.43716	64.02003	100.6029
Tar sands	700	4100[c]	7500	12.80401	74.9949	137.1858
Shale	4400[d]	6100[d]	91800[d]	80.48233	111.5778	1679.154
Gas-conventional	6300	11400	13500	84.94966	153.7184	182.035
Gas in tar sands	40[e]	320[c]	600[e]	0.539363	4.314903	8.090444
Gas in coal seams	30[e]	40[c]	50[e]	0.404522	0.539363	0.674204
Gas in shale	30[e]	40[c]	50[e]	0.404522	0.539363	0.674204
Total	350600	478400	720200	8158.368	11358.13	16657.54

Sources: coal – Cline (1992); all other fossil fuels – Edmonds and Reilly (1985), Table 1-3, p. 8, unless otherwise indicated.

Prices (1979\$) up to: \$10/mcf – gas; \$40/bbl – oil; \$118/metric-ton – U.S. coal.

mcf = thousand cubic feet bbl = barrels

[a] Cline increases coal estimates to allow for U.S. prices up to \$118 per metric ton (1979\$). This price corresponds to Manne and Richels (1990) estimate of a carbon tax of 1988 \$ 250 per metric ton to induce switching to the backstop technology and stabilize carbon emissions at 80% of the 1990 rate (Cline, p. 45, note 5).

[b] Equals best estimate plus Δ, where Δ = best – low.

[c] Average of high and low estimates.

[d] Converted (multiply by 5.8×1.055056, round) from Table 8-3, p. 98. Resource Grade: 25 to 100 gallons of oil per ton of shale. Low: Measured and indicated; Best: measured, indicated and inferred; High: identified and undiscovered.

[e] Converted (multiply by 1.055056, round) from Table 10-3, p. 146.

Table 4. Emission rates.

	lbs CO_2 per MMBtu
Coal	207.7
Oil	156
Gas	115

Sources: Oil and Gas – Hall (1990, Table 1, Notes, p. 287); Coal – Energy Information Agency (1995, p. 363).
To convert from CO_2 to ambient carbon: Multiply by 12/44, the molecular weight of carbon divided by the molecular weight of CO_2.

that link forecasts of future economic activity with the potential use of fossil fuels (Nordhaus & Yohe, 1983; Reilly et al., 1987; Manne & Richels, 1990).

Cline (1992) extrapolates three economic forecasts to provide a sensitivity analysis of nine future emission paths of CO_2, based upon three macro-models and three alternative amounts of economically available fossil fuels. Cline calculates the cumulative addition to atmospheric CO_2, the atmospheric stock, the atmospheric concentration, and the radiative forcing. He then adjusts the radiative forcing to account for other greenhouse warming gases. Finally, Cline considers three alternative increases in global mean temperature, based upon the IPCC (1992) forecast, giving the range of warming from 1.5 to 4.5 degrees Celsius for a doubling of greenhouse gases from the pre-industrial level.

The ratio of ambient CO_2 to the pre-industrial revolution level of 280 parts per million volume (ppmv) – RCO_2 – is a benchmark for general circulation models (GCMs) of the atmosphere and oceans. For a doubling of greenhouse gases – RCO_2 equal to 2 – a warming of 1.5, or 2.5, or 4.5 degrees Celsius corresponds to radiative forcing at 0.375, 0.625, and 1.125 watt per meter squared (per unit of Earth's surface). Given these alternative rates of global warming, Cline has a total of 27 scenarios (three amounts of economically available fossil fuels, three macro-models, three values for climate warming sensitivity). Cline pares this down to nine scenarios by terminating the analysis at year 2275 when the three macro-models predict total emissions at 7,201, 5,992, and 10,141 metric gigatons (M-Gt) of cumulative carbon emissions.

Skeptics of anthropogenic global warming point to the discrepancy between historic warming since the pre-industrial revolution and the predictions by GCMs, given the increase in atmospheric CO_2. The GCM predictions are higher than the actual temperature increase up to 1990. The IPCC (1994) presents a lower range of 1.0 to 3.5 degrees Celsius for RCO_2 equal to 2, based upon possible transient effects of aerosols (IPCC, 1996, Working Group I, p. 39; Working Group III, p. 188). Hall (1996, 1999) adjusts downward Cline's warming forecasts, making them consistent with the IPCC (1996) adjustment.

Recent compilation of data, measuring temperatures in the oceans to a depth of 3000 meters, makes manifest a rising ocean temperature over the last 50 years that is equivalent to a radiative forcing of 0.3 watt per meter squared (Levitus *et al*., 2000). By itself, this finding does not reconcile predictions by global climate models with actual warming between the pre-industrial revolution and today. The reason is that both the upper and deep ocean significantly warmed since the mid–1980s, a period when ambient temperatures also significantly increased. While the heat is coming from somewhere, data do not exist that provide time series of ocean temperature in the very deep ocean, depths below 3000 meters.

Hansen (1999) interprets the recent rapid ambient temperature increase in the 1990s as consistent with predictions by GCMs. Those models were the basis for the original range of warming from 1.5 to 4.5 degrees Celsius for a $2 \times CO_2$ (IPCC, 1990, 1992). Also consistent with Hansen's interpretation, ocean thermal lag is in the order of a half century. The analysis here is based upon the range of global warming of 1.5, 3.0, and 4.5 degrees Celsius for each $2 \times CO_2$ equivalent gases from the pre-industrial level, a warming rate consistent with GCMs. A reasonable assumption is that the ocean thermal lag is a period that lasts for a half-century; the oceans capture 50% of the radiative forcing potential from emitted anthropogenic sources of CO_2 and release the heat 50 years later. That lag is modeled in the analysis that follows.

Coupling ocean and air general circulation models of the globe, GCMs project regional climates, based upon RCO_2 equal to 2, causing the radiative forcing of the atmosphere to increase (IPCC, 1996). Output from the GCMs includes forecast temperature and precipitation; these predictions are then used as inputs for crop simulation models (CSMs). Rosensweig and Parry (1994) and Adams *et al*. (1988, 1990, 1995, 1999) use CSMs to project the changes in potential crop yield and product, for each region in the U.S. with RCO_2 equal to 2; Adams *et al*. (1999) include wheat, corn, soybeans, oranges, tomatoes, pasture, range land, and livestock. Using crop yield and product forecasts from CSMs as input to non-linear programming models of the U.S. and models of international agricultural trade, they go on to estimate changes in the U.S. net producer and consumer surpluses from a doubling of CO_2 equivalent gases.

In their latest work, Adams *et al*. (1999) start with 64 combinations of temperature, precipitation, and ambient CO_2. In essence, the CSMs allow for computer experiments of climate change, accounting for technical efficiencies that capture some adaptation to climate change. They estimate rates of technological change using the past 50 years of data, and adjust agricultural output from the CSMs to account for technological change. Since farmers would select crop combinations as a further adaptation to climate change, they account for economic efficiencies by using quadratic programming and trade models to estimate economic surplus in the U.S. agricultural sector. For each of the 64 climates, Adams *et al*., estimate economic surplus, with and without technological change.

Below, I estimate a generalized power function (GPF) from the data generated by Adams *et al*. (1999). The GPF estimates aggregate agricultural surplus as a function of climate and technological change. Technological change takes two forms: embodied in climate variables capturing the effect of adaptation to climate through specific research and development, and disembodied capturing general improvements in technology. With the estimated GPF, I predict a time path for agricultural surplus, conditional on the following: Cline's (1992) time paths that forecast ambient CO_2, assumptions about precipitation based on GCMs, and mean global temperature forecasts that incorporate a 50-year ocean thermal lag. The ocean thermal lag is consistent with the results by Levitus *et al*. (2000) and ambient temperature increases over the last decade, discussed above. The recoverable resources, macro-models, and values for climate warming and precipitation all combine to allow for a sensitivity analysis.

In an earlier paper (Hall, 1999), I performed a similar analysis. There are several new contributions here. The next section presents a formal representation of the climate model modified to incorporate ocean thermal lag. This is the first time an ocean thermal lag, rather than an ocean thermal sink[2] (Nordhaus, 1994), has been considered in a comparative dynamic analysis of the economic impact of climate. Also new is an adjustment for the difference between mean global temperature and temperature in the U.S., to account for the latitude of the U.S. The temperature data are updated, initialized at year 2000. The forecast of ambient CO_2 is presented in the context of "geoeconomic time".[3] I re-estimate the GPF, improving on the earlier estimation. Finally, the precipitation assumptions are based upon results from GCMs, improving on the sensitivity analysis.

FUTURE GREENHOUSE GAS EMISSIONS AND LAGGED RADIATIVE FORCING

Cline (1992) extrapolates the macro models developed by Reilly *et al*. (1987), Nordhaus and Yohe (1983), and Manne and Richels (1990) to forecast, respectively, metric gigatons of carbon emissions, approximately[4] as follows:

$$\text{RE:} \qquad C_t = (1 + r_t)\, C_{t-1} \tag{1}$$

where $r_t = (0.013643$ for $2000 < t \leq 2025$; 0.008311 for $2025 < t \leq 2050$; 0.006564 for $2050 < t)$ and $C_{2000} = 6.2$.

$$\text{NY:} \qquad C_t = (1 + r_t)\, C_{t-1} \tag{2}$$

where $r_t = (0.025413$ for $2000 < t \leq 2025$; 0.01027 for $2025 < t \leq 2050$; 0.011057 for $2050 < t \leq 2075$; 0.005354 for $2075 < t)$ and $C_{2000} = 5.5$.

$$\text{MR:} \qquad C_t = (1 + r_t)\, C_{t-1} \tag{3}$$

where $r_t = (0.019755$ for $2000 < t \leq 2025$; 0.012048 for $2025 < t \leq 2050$; 0.018511 for $2050 < t \leq 2075$; 0.006256 for $2075 < t)$ and $C_{2000} = 6.5$.

In (1)–(3), C_t is carbon emissions, and the coefficients are the emission growth rates applicable for each time period. The terminal year occurs when the economically available fossil fuels are exhausted. Over time, the slower emission growth rates reflect myriad economic interactions such as rising fossil fuel prices, and market driven substitution to alternative energy sources and energy conservation.

Cline calculates cumulative emissions, E, by:

$$E_t = E_{1990s} + \sum_{s=2000}^{t} C_s, \tag{4}$$

where E_{1990s} is the amount of emissions from fossil fuels used in the 1990s –equal to 55.5, 62.0, and 65.0 metric gigatons of carbon (MgtC) for the three macro models. The constraint on the model is that

$$E_T = 8{,}000,\ 11{,}000,\ \text{or}\ 17{,}000, \tag{5}$$

the cumulative emissions from fossil fuels. The estimates of economically available fossil fuels by Edmonds and Reilly (1985) reflect the process of technological change in the recovery of fossil fuels, future discoveries, and higher prices, all extending recoverable reserves.

The IPCC uses 120 years as the e-folding time atmospheric residence for a pulse increase of CO_2 sufficient for RCO_2 equal to 2. The e-folding time[5] is the number of years at which the biosphere and ocean removes 63% of the increase from pre-industrial levels. For increases greater than RCO_2 equal to 2, the e-folding time increases dramatically. Carbon uptake by plants is limited, as biological material decays. As discussed below, at the Triassic-Jurassic boundary, CO_2 was so high that climate effects lead to the disappearance of most species. "Kasting and Walker (1992) point out that the assumption of linearity may seriously understate the atmospheric retention of carbon. Kasting suggests that a pulse of CO_2 emissions that is three times pre-industrial concentrations would have an atmospheric lifetime (e-folding time) between 380 and 700 years" (Nordhaus, 1994, note 4, p. 26). To model the atmosphere beyond a doubling of CO_2, the model proposed by Nordhaus is mis-specified. For a tripling ($RCO_2 = 3$) or larger, as in Cline's model, a reasonable assumption is that 50% of the emissions remain in the atmosphere, so the cumulative additions, A, to atmospheric carbon are given by

$$A_t = E_t/2. \tag{6}$$

The atmospheric stock, S, of carbon in any year equals the stock in the initial year (750 in 1990) plus the cumulative additions:

$$S_t = 750 + A_t \tag{7}$$

The atmospheric concentration of CO_2, CO_2 in parts per million volume (ppmv), is found by multiplying the 1990 ratio of concentration (353 ppmv) to stock (750 MgtC):

$$CO2_t = 353S_t/750 \tag{8a}$$

The cumulative atmospheric concentration ultimately depends on the amount of economically available fossil fuels. For the three values given in equation (5), the corresponding atmospheric concentration of CO_2 equals 2,400, 3,200, and 4,500 ppmv. Define $RCO2_t$, the ratio of CO_2 to the pre-industrial level, by:

$$RCO2_t \equiv CO2_t/CO2_0 \tag{8b}$$

where the denominator is the ambient concentration in the late 1800s.

The three models predict RCO_2 equal to 9, 11, and 16. To get a sense of the scale involved, Fig. 1 from Berner (1997) shows atmospheric concentrations measured in RCO_2 over the past 600 million years. The macro models forecast that economic forces will cause, within the next 325 to 350 years, the atmosphere to revert to an era never experienced by most plants and animals living today, levels not experienced by earth at any time during the last 375 to 425 million years. Figure 2 gives the predicted values over the next 325 to 350 years.

Cline (1992, p. 25) calculates CO_2-related radiative forcing, R^C (in watt per meter squared), above pre-industrial levels as follows:

$$R^C_t = 6.3 \log(CO2_t/CO2_0) \tag{9}$$

where $CO2_0$ is the pre-industrial level (279ppmv).

A convention in the literature is to refer to "CO_2 equivalent gases" to account for other greenhouse warming gases humans emit due to economic activity.

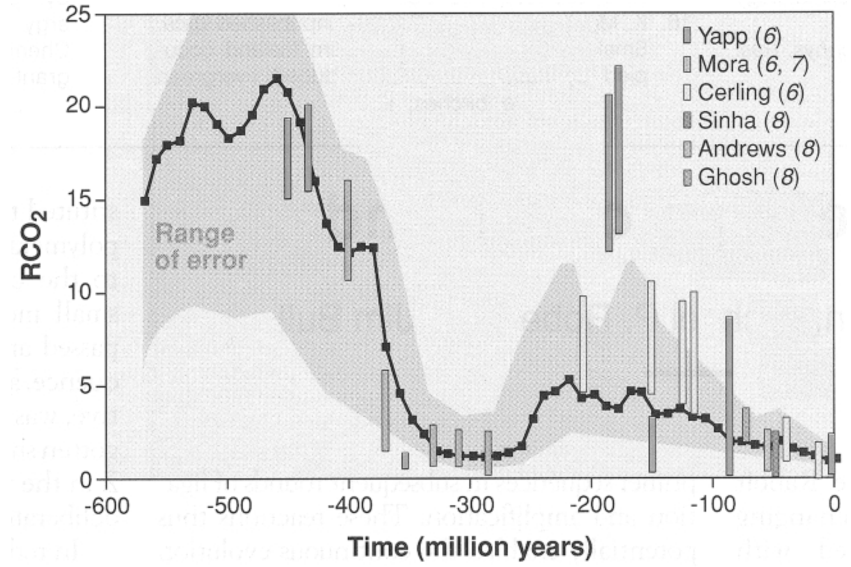

Fig. 1. Atmospheric CO_2 vs. time for the Phanerozoic (past 550 million years). The parameter RCO_2 is defined as the ratio of the mass of CO_2 in the atmosphere at some time in the past to that at present (with a pre-industrial value of 300 parts per million). The heavier line joining small squares represents the best estimate from GEOCARB II modeling (*10*), updated to have the effect of land plants on weathering introduced 380 to 350 million years ago. The shaded area encloses the approximate range of error of the modeling based on sensitivity analysis (*10*). Vertical bars represent independent estimates of CO_2 level based on the study of paleosols. Reprinted with permission from Berner, R. A. 1997. "The Rise of Plants and Their Effect on Weathering and Atmospheric CO_2." Science 276(25): 544–546. April 25. Copyright American Association for the Advancement of Science.

Cline (1992) adjusts CO_2 radiative forcing upward to estimate radiative forcing, R^E, from all anthropogenic greenhouse gases. Cline's adjustment is based upon data from IPCC (1992) for values of R^C up to 6.8 wm^{-2}. For the years 1990 and 2000, Cline gives the values for R^E equal to 2.5 and 2.8 watt per meter squared, respectively. Keeping in mind that the Montreal Protocol and related treaties reduce CFC's and other gases by 2000 and 2005, a good approximation to Cline's value for R^E after the year 2000 can be found by:

$$R^E_t/R^C_t = 1.447 \exp[k(6.8 - R^C_t)] \text{ for } R^C < 6.8 \text{ and } t \geq 2000. \qquad (10a)$$

The value for k can be found by using the values in Cline for R^E and R^C, when $R^C < 6.8$ and $t \geq 2000$, in the following:

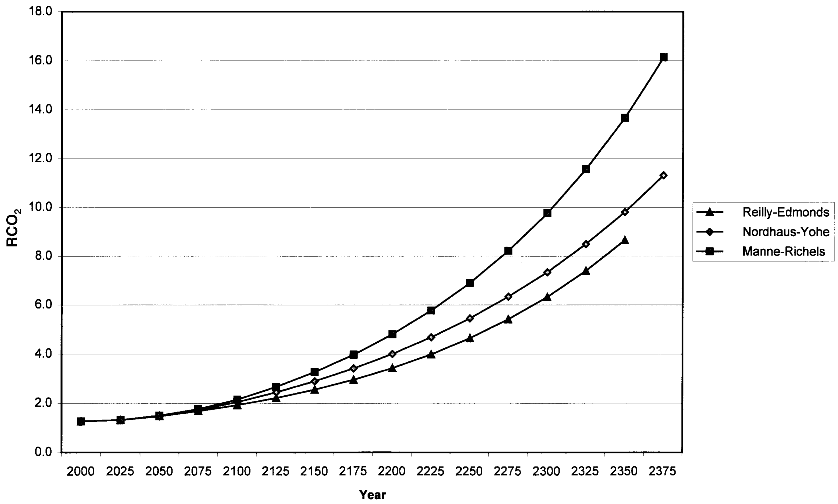

Fig. 2. RCO_2 – Ratio of Atmospheric Concentration of CO_2 to Pre-industrial Level.

$$k = [\log(R^E/1.447R^C)]/(6.8 - R^C). \tag{10b}$$

The value for k is approximately 0.0277503. For values above 6.8 wm^{-2}, Cline multiplies radiative forcing from CO_2 by 1.447 to obtain CO_2 equivalent radiative forcing, R^E, accounting for other greenhouse gases,

$$R^E_t/R^C_t = 1.447 \text{ for } R^C \geq 6.8. \tag{10c}$$

Cline (1992) calculates the change in mean global temperature in degrees Celsius for three alternative climate sensitivities, a 1.5-degree increase for a doubling of radiative forcing, a 2.5-degree increase, and a 4.5-degree increase. The pre-industrial value for radiative forcing equals 2 wm^{-2}, so a doubling is 4 wm^{-2}. For example, for a 2.5 degree sensitivity, the change in temperature is given by:

$$\Delta T_t = 2.5R^E_t/4 \tag{11}$$

To compare Cline's model with other models that extend beyond a doubling, note that by substitution among equations (8b) and (9) into (11), the temperature change due to CO_2 equals 3.9 log(RCO_2), which corresponds to the "formulation from Z. Kothavala, R. J. Oglesby, and B. Saltzman [*Geophys. Res. Lett.* **26**, 209 (1999)]: $\Delta T = 4.0 \log(RCO_2)$" (McElwain, Beerling & Woodward, 1999, footnote 24, p.1389).

For 1990, the change in temperature is initialized at zero, and for the year 2000 the change in temperature is initialized at 0.6 degrees Celsius (Hansen, 1999).

Nordhaus presents a two-equation exponential decay model from early work by Schneider and Thompson (1981) to describe the process by which the ocean captures heat. The model allows for heat to be released eventually, but the Nordhaus model is more accurately described as an ocean thermal sink rather than an ocean thermal lag. Nordhaus specifies the e-folding time equal to 500 years, so increases in deep ocean temperature decay back toward the pre-industrial revolution level outside the time frame of any model. His specification is inconsistent with historical data.[6] More problematic for analysis of RCO_2 greater than 2, "the striking finding of the 4 X CO_2 run is that the atmosphere-ocean system settles into a second, locally stable equilibrium with a different ocean circulation" (Nordhaus, 1994, note 8, p. 35–36). Consequently, an exponential decay model mis-specifies the geophysical system for models that extend to a quadrupling ($RCO_2 = 4$) or beyond.

An exponential decay process presumes a single equilibrium for biogeophysical processes. Moreover, values for the parameters can, for all practical purposes, treat biogeophysical processes as a heat sink. It is more reasonable to incorporate a thermal lag into climate models. Next I introduce a simple way of capturing the idea of ocean thermal lag into the model, where one half of the radiative forcing is stored in the ocean for 50 years and then released. This is consistent with the finding by Levitus *et al*. (2000). They find that from 1948 to 1998 the heat content of the top 3000 meters of the oceans has increased by 2×10^{23} joules, corresponding to a warming rate of 0.3 watt/m^2 or about one half of the warming predicted by GCMs for the last century. Moreover, in the last decade of the analysis by Levitus *et al*., from the late 1980s to 1998, ambient temperatures increased by about one degree Fahrenheit. To account for this lag, adjust equation (11) as follows, dropping the superscript on radiative forcing, R:

$$\Delta T_t = 2.5R_t/8 \qquad \text{for } t < 2040, \text{ and} \qquad (12a)$$

$$\Delta T_t = 2.5(R_t + R_{(t-50)})/8, \qquad \text{for } t > 2040. \qquad (12b)$$

For a doubling of CO_2 equivalent gases, Table 5 presents a comparison of estimates of mean global temperature to U.S. average temperature forecasts. The comparison is among three GCMs that forecast temperature changes for a $2 \times CO_2$. Because the U.S. is at higher latitude, the models predict greater warming for the U.S. than the global mean. The ratio of mean global temperature change to U.S. temperature change, averaged over the GCMs, equals:

Table 5. Comparison of GCMs for a Doubling of CO_2 Equivalent Gases.

General Circulation Model (GCM)	Δ°C global mean[1]	%Δ precipitation global mean[1]	Δ°C U.S. Average (Winter, Summer)[2]	%Δ precipitation U.S. Average (Winter, Summer)[2]
Goddard Institute for Space Studies (GISS)	4.20	11%	4.32 (5.46, 3.50)	20% (13, 24)
Geophysical Fluid Dynamics Laboratory (GFDL)	4.00	8.3%	5.09 (5.25, 4.95)	9% (19,–8)
Oregon State University (OSU)	2.84	7.8%	2.95 (2.95, 3.10)	17% (24, 11)

[1]*Source*: Williams et al. (1996).
[2]*Source*: Adams et al. (1988).

$$\Delta_{US}T/\Delta_G T = 1.12. \tag{13}$$

The adjustment for latitude allows us obtain average U.S. temperatures:

$$\Delta_{US}T_t = 1.12[2.5R_t/8] \qquad \text{for } t < 2040, \text{ and} \tag{14a}$$

$$\Delta_{US}T_t = 1.12[2.5(R_t + R_{(t-50)})/8], \qquad \text{for } t > 2040. \tag{14b}$$

Averaged over the 30 year period from 1951 to 1980, the mean global temperature is estimated at about 15 degrees Celsius (table, p. xxxvii, IPCC, 1990). Consistent with equation (13), the average U.S. temperature for 1990 is initialized at 12% greater, or 16.8 degrees. The future temperatures for each scenario are calculated by adding the change to the initial temperature.

$$T_t = 16.8 + \Delta_{US}T_t \tag{15}$$

The IPCC (1990) assessment, based on a doubling, projects U.S. precipitation to increase from 0 to 15% in winter and decrease from 5 to 10% in summer. In a review of 16 GCMs, Williams, Shaw and Mendelsohn (1996) present mean global temperature increases and precipitation. The temperature increase averaged across GCMs is about 3.5 degrees Celsius, with an increase in precipitation equal to 7%. But there are duplicate numbers for mean global temperature and precipitation increases, presumably because some of the models are closely related in their construction – close derivatives of one, another. Mendelsohn, Nordhaus and Shaw (1994) state they are following the IPCC with an 8% increase in precipitation corresponding to a 3 degree Celsius warming for a doubling of CO_2 equivalent gases.

Averaging across the three GCMs in Table 5, the percentage increase in U.S. precipitation equals 15.33%, with a corresponding average across GCMs of U.S. temperature increases equal to 4.12 degrees Celsius. The change in summer rainfall varies across the models, from a low of an 8% decrease to a high of a 24% increase. This is the basis for the sensitivity analysis presented below. Let 50 inches annually be the initial value for average U.S. precipitation. In the mid-case scenario, precipitation will be proportionately increased by 15.33% per increase in temperature of 4.12 degrees Celsius. For the years from now until a temperature increase of that amount, precipitation, P, equals:

$$P_t = 50[1 + 0.1533(T_t - 16.8)/4.12]. \tag{16a}$$

The dry scenario is an 8% decrease in precipitation for an increase of 4.12 degrees:

$$P_t = 50[1 - 0.08(T_t - 16.8)/4.12]. \tag{16b}$$

The wet scenario is a 24% increase in precipitation for an increase of 4.12 degrees:

$$P_t = 50[1 + 0.24(T_t - 16.8)/4.12]. \tag{16c}$$

Equations (16a–c) are valid for temperature increases for the first incremental increase of 4.12 degrees, but should be compounded for each additional increment of 4.12 degrees. Without compounding, for example, precipitation could become negative in the dry scenario. To generalize for compounding, precipitation is given by

$$P_t = P_{t0}\,[1 + r(T_t - 16.8)/\Delta T] \text{ for } T_{1990} + N_t\Delta T \le T \le T_{1990} + (N_t + 1)\Delta T, \tag{17a}$$

where

$$P_{t0} = 50(1 + r)^{N_t}. \tag{17b}$$

In equations (17a) and (17b), $T_{1990} = 16.8$, $\Delta T = 4.12$, and $r = \%\Delta P$. N_t is the number of times temperature has increased from 1990 by an increment of $\Delta T = 4.12$. With an Excel IF statement, N_t can be written as follows:

$$N_t = \text{IF}(D > 7{,}7, \text{IF}(D > 6{,}6, \text{IF}(D > 5{,}5, \text{IF}(D > 4{,}4,$$
$$\text{IF}(D > 3{,}3, \text{IF}(D > 2{,}2, \text{IF}(D > 1{,}1{,}0))))))), \tag{17c}$$

where $D = (T_t - T_{1990})/\Delta T$.

Equations (8), (15), and (17) give a forecast that includes the combination of the following variables: ambient CO_2 (equation 8), average U.S. temperature (equation 15), and average U.S. precipitation. If we had an aggregate agricultural surplus function that predicts agricultural surplus as dependent upon these three variables, we could forecast the time path of the surplus.

ADAMS *ET AL*. (1999) DATA AND ESTIMATION OF AGGREGATE AGRICULTURAL SURPLUS

Adams *et al*. (1999) generate data from a combination of crop simulation models, non-linear programming models, and agricultural trade models. Their unique approach includes adaptation by farmers to climate change, and allows for technological change. I use their data to estimate aggregate agricultural surplus as a function of ambient CO_2, temperature, precipitation, and the rate of technological change. Using the estimated aggregate agricultural surplus function, in the next section I predict future surplus conditional on the climate forecasts from equations (8), (15), and (17). By altering the forecasts, the comparative dynamics show the impact on U.S. agriculture from climate change.

A. Adams et al. Data[7]

The publication by Adams *et al*. (1999) is the culmination to date of their previous work (Rosensweig & Parry, 1994; Adams *et al*., 1988, 1990, 1995). Their approach is to simulate crop yields using dynamic growth Crop Simulation Models (CSMs). They do so for various combinations of temperature, ambient CO_2, and precipitation, letting the computerized CSMs simulate global climate experiments. Then they input changes in crop yields into an economic quadratic programming model of the agricultural sector. The economic model allows farmers to adapt the mix of crops to maximize profit, given the changes in yield and prices that result from global warming and the demand for food.

The CSMs originally projected the impact of warming on soybeans, corn and wheat (Adams *et al*., 1990); later (Adams *et al*., 1999) they added cotton, potatoes, tomatoes and citrus, forage and livestock. The CSMs account for solar radiation, precipitation, temperature, soil properties that capture moisture, and the enhanced yield "fertilizing effect" of increased CO_2 in the atmosphere. The results from the CSMs are extrapolated to other crops in the economic model.

Adams *et al*. (1999) consider 64 climate configurations: precipitation changes (− 10, 0, 7, and 15%), temperature changes (0, 1.5, 2.5 and 5.0°C), and ambient CO_2 fertilization (at 355, 440, 530, and 600 ppmv). They assume that each configuration is spread uniformly across the U.S. They calibrate the crop simulation models for each region in the U.S., changing present climate data by these amounts.

The speed of wheat, corn, and soybean crop development increases with temperature, causing yield decreases and higher water demand. Increases in ambient CO_2 decrease water demand by increasing the efficiency of water use. Cotton has decreased yield from temperature, since it reaches maturity in fewer days, but increased yield from precipitation. For irrigated areas, no change in cotton yield is expected from changing precipitation. Similarly, potatoes, tomatoes, and citrus are modeled to have no effect from precipitation since they are irrigated. Adams *et al.* (1999) assume increases in citrus yield from CO_2, although the reason is "poorly substantiated in the present literature". Increases in temperature cause the loss of a suitable dormant period, decreasing citrus yield in the south and potentially increasing yield in the north, but potential migration is constrained because sandy soils don't exist in the north. Potato yields fall with temperature, and rise with CO_2. Tomato yields increase with CO_2 and increase with temperature up to a + 1.5 to 2.5 degree rise, then yields fall.

Adams *et al.* (1999) use two CSMs for forage production and livestock, one for the more arid west of the U.S., and another for the east. These models were calibrated for various locations, using existing weather data to get a baseline prediction, and then modifying the amounts of precipitation and temperature. For example, changes in precipitation were "applied uniformly to each monthly value". The impacts of temperature, precipitation, and CO_2 fertilization varied by location, with increases in precipitation generally increasing yields, CO_2 fertilization increasing yields, and the effect of temperature mixed, depending on the existing temperature and the size of the increase. Averaged across regions, they predict increases in yields; where predicted yields fall, the amounts are small, but other locations are projected to have rather large increases in yields, depending on the climate configuration. Direct effects on livestock include appetite-suppressing temperature increases, and decreased energy needed in the winter to stay warm. Averaged across regions and effects, they predict falling livestock production.

Adams *et al.* (1999) account for changes in technology and adaptation to global warming. There will be adjustments to warming – R&D will help crops to migrate, and will develop heat tolerant and drought tolerant varieties. Farmers will adjust inputs, the timing of planting and harvesting. Crop migration is constrained by soil barriers with significant yield losses. Adams *et al.*, rely on time series regression to relate improvements in yields over time, and crop migration. They use cross section regression to account for adjustments and adaptation of farmers to regional temperature differences. They compare the crop simulation results to results from regression of county yield on temperature and precipitation. Yields do not fall as much with increases in temperature (but that could be due to correlation with solar radiation). For some regions, wheat yields rise and then fall with rising temperature. Regressions show yields rising with precipitation, but not by as much as projected by CSMs. Yields fall with April precipitation, reflecting the monsoon effect; intense precipitation damages crops. Based on their examination of these results (not presented but discussed), they assume that at least 50% of the CSM-projected damage from 2.5 degrees Celsius mean global warming can be mitigated through soil amendments, irrigation, crop migration, and technological change. For 5 degrees, they assume 25% mitigation of yield losses.

The economic model (Adams *et al.*, 1999) accounts for differences in crop demand, the impact of precipitation on surface and ground water supply, costs of surface and ground water, crop selection to maximize consumer and producer surplus, costs of feed for livestock as a secondary industry, regional and international trade. The model allows for future trends of basic variables, based upon trends over the past 40 years, to account for increases in demand through population growth, quantities of inputs, and import levels and supplies. Inputs are adjusted to account for changes in yields over time. Forecasts of economic surplus are developed for the years 1990 and 2060, with and without the effects of climate change.

Adams *et al*. (1999) calculate net consumer and producer surplus for each region of the U.S., as given in the economic model, and sum the impacts to obtain the aggregate impact on the U.S. (including foreign consumer surplus for exports). This is repeated for each of the 64 climate combinations. For each year, 1990 and 2060, they then regress the economic value against precipitation, temperature and ambient CO_2, using a quadratic form, and also a simple analysis of variance. The result is a climate change response function. For each climate combination, they compare the predicted net surplus with the prediction conditioned on 355 ppmv of CO_2 (today's ambient concentration), 0% change in precipitation, and 0% change in temperature. The 1990 regression results perform a comparative static experiment, predicting the impact of climate change if it were imposed on agriculture today, and the agricultural industry could instantaneously respond. The 2060 regression results perform the comparative static experiment of imposing climate change over time, with research and development to adapt, and comparing agricultural surplus in 2060 to the 2060 surplus if there were no warming, but research and development were to continue to improve yields.

The comparative static results for 1990 conditions are smaller relative to the comparative static results for the year 2060. The impact of global warming is larger given the adjustments for technology and economic conditions. Whether the impact of global warming is positive or negative depends on the climate configuration. Overall, the results by Adams *et al*. (1999) indicate that the impact is positive, but there are some climate combinations they consider where the opposite result is obtained. For further details about their approach and some additional results, see Adams *et al*. (this volume).

B. Aggregate Agricultural Surplus

I estimate a generalized power function (GPF) with the data generated by Adams *et al*. (1999) from both years, 1990 and 2060. The GPF is of the form:

$$S = \beta_0 X^{\beta X} \exp(\phi X) + \varepsilon) \quad (18)$$

where β_0 is a scalar, β and ϕ are vectors, and X is a matrix of explanatory variables. This function is quite general (de Janvry, 1971). The Cobb-Douglas is a special case.

Since a power function cannot include zero values for the explanatory variables, the Adams *et al*. (1999) data cannot be used directly. Adams *et al*., present the change in surplus from a base case, given changes in temperature, ambient CO_2, and precipitation. The 1990 values for surplus, temperature, and precipitation must be added to the data in Adams *et al*. The initial values for temperature and precipitation are 16.8 degrees Celsius (equation 15 above) and 50 inches, respectively. Adams *et al*. use a linear-dummy variable specification to estimate the impact of temperature, precipitation, and CO_2 fertilization effect on total surplus (consumer, producer, foreign) for U.S. agriculture. The intercept coefficient in Adams *et al*. (1999, Appendix, Table 3) is 1239.412, which is the value of surplus in millions of 1990 \$ for U.S. agriculture. Similarly, the intercept coefficient in year 2060 is 1750.594, which is the total surplus for the year 2060 in millions of 1990 \$ in the absence of climate change. To generate the aggregate surplus data, for each of the 64 climate combinations, I add the Adams *et al*., estimated changes in 1990 to 1239.412, and the estimated 2060 changes to 1750.594.

A simple version of the GPF that captures the effect of technological change is given by:

$$S = \beta_0 P^{\beta 1 + \beta 2Y} T^{\beta 3 + \beta 4Y} C^{\beta 5 + \beta 6Y} \exp(\beta_7 P + \beta_8 T + \beta_9 C + \beta_{10} Y + \varepsilon). \quad (19)$$

where S = producer plus consumer plus foreign surplus, P = precipitation, T = temperature in degrees Celsius, C = ambient CO_2 in ppmv of carbon, and Y = number of years (set to zero for 1990, increasing by one for each 5-year period of the analysis).

This function has the desirable property that the marginal surplus (with respect to the climate-input variables) can take on 15 shapes (see Hall, 1999),

Table 6. GPF Equation (19).

Variable	Coefficient	Std. Error	*t*-Statistic	Prob·
C	2.933413	1.174671	2.497220	0.0139
LNP	0.412327	0.325362	1.267287	0.2076
Y*LNP	0.001703	0.001774	0.959949	0.3391
LNT	1.196930	0.282567	4.235920	0.0000
Y*LNT	–0.001613	0.001696	–0.950998	0.3436
LNCO2	0.122423	0.075481	1.621892	0.1075
Y*LNCO2	0.001416	0.000808	1.752045	0.0824
P	–0.006399	0.006387	–1.001853	0.3185
T	–0.069016	0.014651	–4.710636	0.0000
CO2	–0.000136	0.000162	–0.839087	0.4031
Y	0.014576	0.009875	1.476111	0.1426
R-squared	0.995498	Mean dependent var		7.299164
Adjusted R-squared	0.995110	S. D.dependent var		0.179658
S. E. of regression	0.012564	Akaike info criterion		–5.833392
Sum squared resid	0.018310	Schwarz criterion		–5.587045
Log likelihood	381.4204	F-statistic		2564.912
Durbin-Watson stat	1.796943	Prob(F-statistic)		0.000000

Dependent Variable: LNS
Method: Least Squares
Date: 04/03/00 Time: 17:29
Sample: 1 127
Included observations: 127

only four of which are consistent with theory. These four cases have the desirable property of convexity: diminishing marginal surplus. We should expect that total surplus will rise to some maximum with increases in any of the climate variables (temperature, precipitation, and ambient CO_2), and then fall thereafter. A good test of the model is that the results are consistent with one of these four cases. If the hypotheses are rejected that the model takes on one of the four shapes, then we can reject the functional form.[8] After taking logs of both sides, I use ordinary least squares to estimate the parameters in equation (19), and present the results in Table 6. The alternative shapes of the functions are consistent with the hypothesized impacts of precipitation, temperature and ambient CO_2 on agricultural surplus.

Technological change can be both embodied and disembodied. Disembodied technological change ($\beta_{10} \neq 0$) allows for the marginal surplus curve to increase irrespective of the climate variables, while embodied technological change ($\beta_2, \beta_4, \beta_6 \neq 0$) has its influence through one or more of the climate variables.

Table 7. GPF Equation (20).

Variable	Coefficient	Std. Error	*t*-Statistic	Prob
C	2.961494	1.171963	2.526953	0.0128
LNP	0.416651	0.324943	1.282230	0.2023
LNT	1.179967	0.281908	4.185643	0.0001
LNCO2	0.120769	0.075405	1.601608	0.1119
Y*LNCO2	0.001387	0.000807	1.719232	0.0882
P	–0.006258	0.006380	–0.980820	0.3287
T	–0.068699	0.014636	–4.693771	0.0000
CO2	–0.000132	0.000161	–0.817886	0.4151
Y	0.016712	0.004973	3.360335	0.0010
R-squared	0.995428	Mean dependent var		7.299164
Adjusted R-squared	0.995118	S. D.dependent var		0.179658
S. E. of regression	0.012553	Akaike info criterion		–5.849557
Sum squared resid	0.018593	Schwarz criterion		–5.648001
Log likelihood	380.4469	F-statistic		3211.577
Durbin-Watson stat	1.777927	Prob(F-statistic)		0.000000

Dependent Variable: LNS
Method: Least Squares
Date: 04/03/00 Time: 17:48
Sample: 1 127
Included observations: 127

Embodied technological change can be interpreted as an adaptation to global warming – technological change embodied in precipitation, ambient CO_2, and temperature. Disembodied technological change can be interpreted as due to general improvements in agricultural productivity. Testing the hypothesis that there is no technological change, I reject the hypothesis that there is no disembodied technological change, and the hypothesis that there is no technological change embodied in ambient CO_2. The hypotheses are not rejected for no technological change embodied in temperature or precipitation (Table 6).

Accepting the null hypothesis that there is no technological change embodied in precipitation, similarly for temperature, the model is re-specified. In this specification, there is technological change embodied in CO_2 and disembodied technological change:

$$S = \beta_0 \, P^{\beta 1} T^{\beta 2} C^{\beta 3 + \beta 4 Y} \exp(\beta_5 P + \beta_6 T + \beta_7 C + \beta_8 Y + \varepsilon) \qquad (20)$$

Table 7 presents the results. From Table 7 and equation (20), it is possible to estimate the optimal values for precipitation, temperature, and ambient CO_2.

These values are found by maximizing (20) with respect to P, T, and C. The optimal values are given by:

$$P^* = \beta_1/-\beta_5 = 66.58 \tag{21a}$$

$$T^* = \beta_2/-\beta_6 = 17.18 \tag{21b}$$

$$C^* = (\beta_3 + \beta_4 Y)/-\beta_6 = 914.92 + 10.51Y \tag{21c}$$

where Y increases by one for every five years. From equation (21b), we can conclude that it is already almost as warm as is optimal. In fact, another increase by one-half degree Celsius and global warming will begin to reduce agricultural surplus in the U.S. The potential benefits from global warming to U.S. agriculture are not from the change in temperature, but from possible increases in precipitation and from CO_2 fertilization that will occur simultaneously with global warming. In addition, over time we will see an increase in the marginal surplus from CO_2 fertilization as we learn how to better take advantage of ambient CO_2, and adapt to climate change.

COMPARATIVE DYNAMICS OF DAMAGE TO AGRICULTURE FROM CLIMATE CHANGE

In this section, the estimated agricultural surplus function given by equation (20) predicts future surplus, conditional on the climate forecasts from equations (8), (15), and (17), and the comparative dynamics show the impact on agriculture from climate change.

For the case of no climate change (NC) and the three sets of geoeconomic assumptions given in Table 8, MR, RE, and NY, the predicted surplus for each year Y is given by:

$$\begin{aligned} S_{NC} = \exp[&\beta_0 + \beta_1 \log(50) + \beta_2 \log(16.8) + \beta_3 \log(353) + \beta_4 Y \log(353) \\ &+ \beta_5 50 + \beta_6 16.8 + \beta_7 353 + \beta_8 Y] \end{aligned} \tag{22}$$

$$\begin{aligned} S_{RE} = \exp[&\beta_0 + \beta_1 \log(P_{RE}) + \beta_2 \log(T_{RE}) + \beta_3 \log(C_{RE}) + \beta_4 Y \log(C_{RE}) \\ &+ \beta_5 P_{RE} + \beta_6 T_{RE} + \beta_7 C_{RE} + \beta_8 Y] \end{aligned} \tag{23a}$$

$$\begin{aligned} S_{MR} = \exp[&\beta_0 + \beta_1 \log(P_{MR}) + \beta_2 \log(T_{MR}) + \beta_3 \log(C_{MR}) + \beta_4 Y \log(C_{MR}) \\ &+ \beta_5 P_{MR} + \beta_6 T_{MR} + \beta_7 C_{MR} + \beta_8 Y] \end{aligned} \tag{23b}$$

$$\begin{aligned} S_{NY} = \exp[&\beta_0 + \beta_1 \log(P_{NY}) + \beta_2 \log(T_{NY}) + \beta_3 \log(C_{NY}) + \beta_4 Y \log(C_{NY}) \\ &+ \beta_5 P_{NY} + \beta_6 T_{NY} + \beta_7 C_{NY} + \beta_8 Y] \end{aligned} \tag{23c}$$

The forecast given by equation (22) presents the effect of technological change over time on the time path of agricultural surplus.

Table 8. Geoeconomic Assumptions

	Macro Economic Model	Temperature increase for a doubling of CO_2 equivalent gases	Economically available fossil fuels in metric gigatons of carbon
Dry climate: − 8%	RE	1.5°C	8,000
precipitation increase	MR	2.5°C	11,500
per 4.12°C increase	NY	4.5°C	17,000
Ave. climate: + 15%	RE	1.5°C	8,000
precipitation increase	MR	2.5°C	11,500
per 4.12°C increase	NY	4.5°C	17,000
Wet climate: + 24%	RE	1.5°C	8,000
precipitation increase	MR	2.5°C	11,500
per 4.12°C increase	NY	4.5°C	17,000

RE: Reilly, Edmonds, Gardner, and Brenkert (1987)
MR: Manne-Richels (1990)
NY: Nordhaus-Yohe (1983)

Each of the three macro models in equations (23a-c) has a separate forecast for carbon emissions. The ambient concentration of CO_2 is from equation (8) and the changes in average U.S. temperature are from equation (14), forecast for the next 300 to 325 years. There are three alternative temperature forecasts summarized in Table 8. The time path of carbon emissions is lowest for the RE macro-model; the mid-range is the MR macro-model; the highest is the NY macro-model. Since the carbon emissions determine the temperature, I couple the most optimistic macro-model (RE) with the most optimistic temperature sensitivity assumption (a 1.5 degrees Celsius global increase for a CO_2 equivalent doubling), and the most optimistic assumption about cumulative carbon emissions (7,000 metric tons). Similarly, I couple the mid-range MR model with the mid-range temperature sensitivity assumption (a 3.0 degrees Celsius global increase for a CO_2 equivalent doubling), and the mid-range assumption about the extent of economically available fossil fuels. I couple the most pessimistic macro model, NY, with the most pessimistic temperature sensitivity assumption (a 4.5 degrees Celsius global increase for a CO_2 equivalent doubling), and the most pessimistic assumption about the extent of economically available fossil fuels. In this fashion, I summarize and encompass 27 possible combinations with three combinations of geoeconomic assumptions.

The effect of precipitation on the results is complex because, from equation (21a), the optimal amount of precipitation is significantly higher than at present. Consequently, Figs 3–5 present a total of nine results, based upon the assumptions in Table 8.

Figures 3–5 show the time paths of agricultural surplus. Figures 6–8 show the change in surplus from the case of no climate change. All of the temperature forecasts include the lagged effect of one half of the radiative forcing for 50 years. The calculations are for the years 1990, 2000, 2025, etc., in 25 year intervals, until fossil fuels are economically exhausted. The switch to alternative energy sources occurs between the years 2300 and 2325, depending on the macro-model and the economically available fossil fuels.

In some respects, these results confirm analyses by Adams *et al*. (1999) and Mendelsohn, Nordhaus and Shaw (1994), but in other respects the results provide new insights. Consistent with earlier studies, if temperature increases are small, there may be a small near-term benefit to U.S. agricultural surplus. If temperature rises between 3 to 4.5 degrees Celsius per RCO_2, however, then eventually there is a significant loss. Moreover, the loss rapidly grows to substantial proportions. At the high end of temperature increases, agricultural surplus stops growing and may even collapse altogether.

If climate change is drier or wetter than expected (Figs 3 and 5), then for all cases, there is an eventual loss to U.S. agricultural surplus. All the greater the

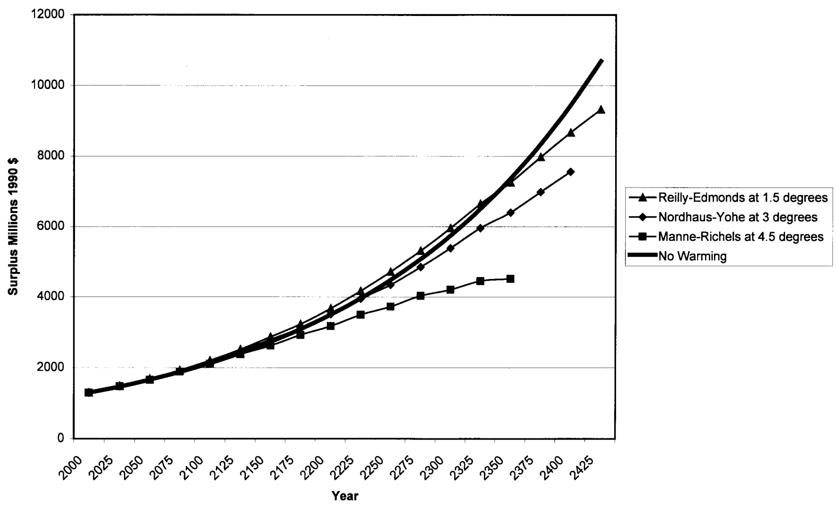

Fig. 3. Agricultural Surplus for Dry Climate.

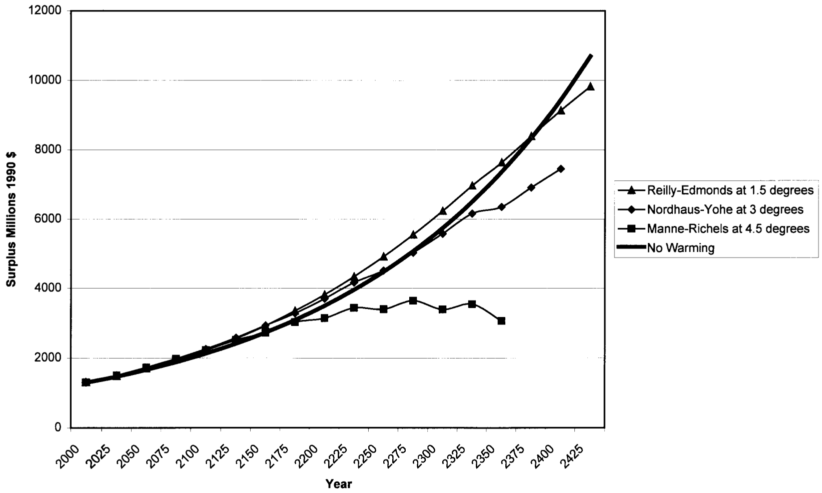

Fig. 4. Agricultural Surplus for Average GCM Precipitation.

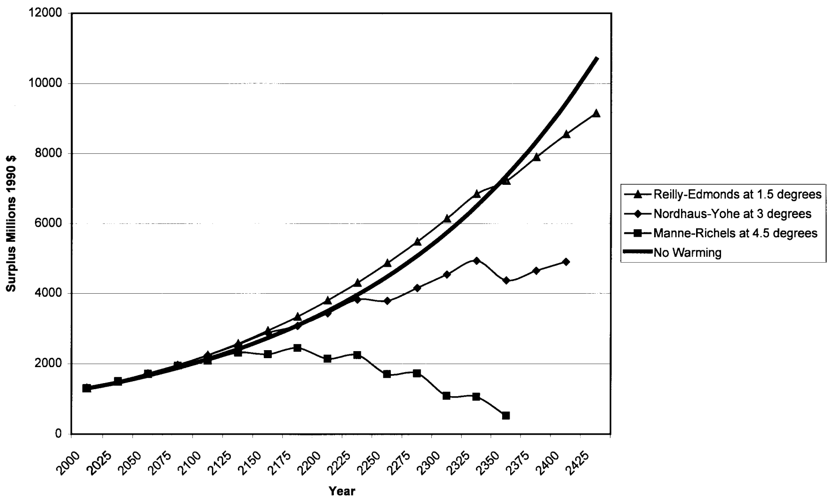

Fig. 5. Agricultural Surplus for Wet Climate.

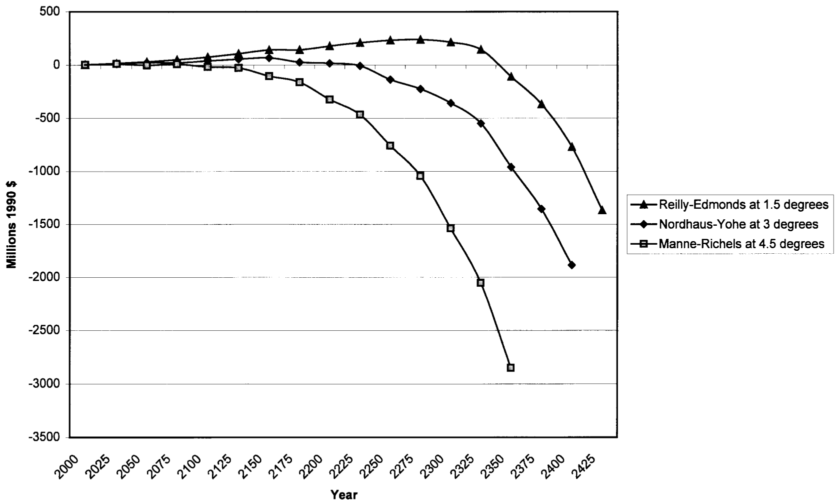

Fig. 6. Change in Surplus for Dry Climate.

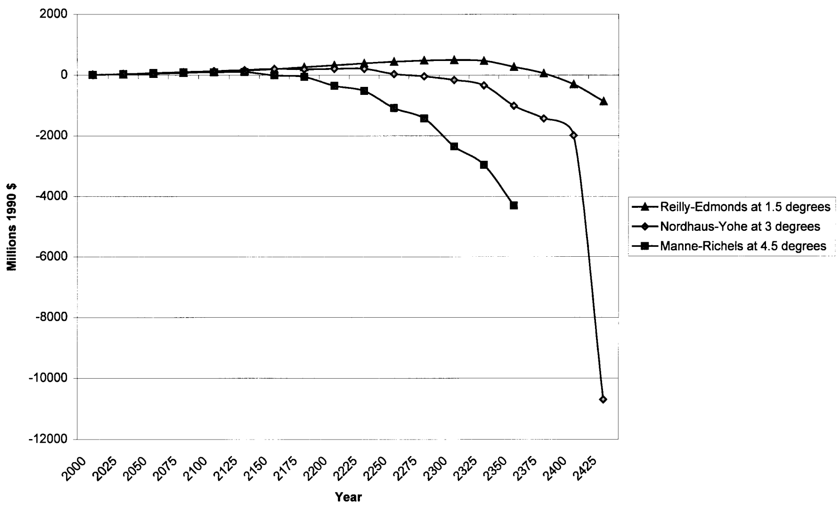

Fig. 7. Change in Surplus for Average GCM Climate.

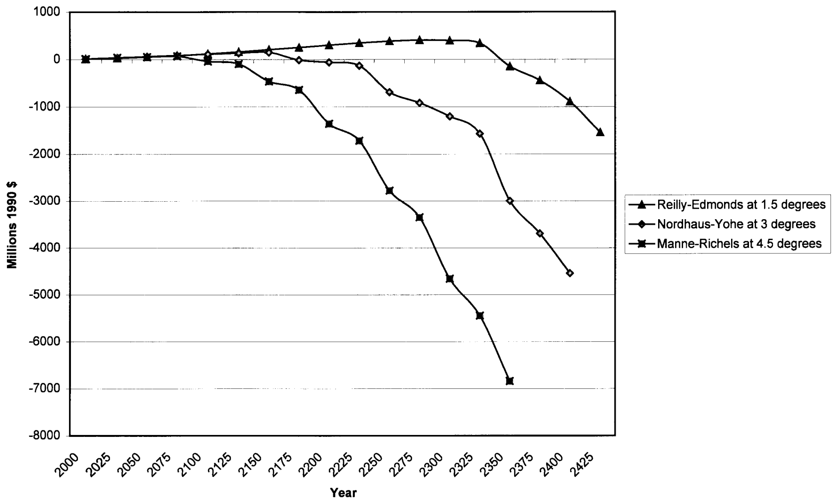

Fig. 8. Change in Surplus for Wet Climate.

temperature increase for a doubling of CO_2 equivalent gases, all the sooner the losses begin.

These results can be contrasted with my earlier work (Hall, 1999). With a 50-year ocean thermal lag, damage does not occur as soon as without the lag. On the other hand, if we delay any significant policy intervention until we detect damage, these results show that it is too late to prevent significant losses in agricultural surplus. Under all scenarios, once damage begins, within the following 50 years the damage becomes pronounced. There may be an equivalent lag due to political-economic inertia that delays policy intervention well after damage is detected.

The ownership of fossil fuels is the source of vested interests with the political ability to stop or delay effective policy. In addition, once we decide to subsidize research and development of alternative energy technologies, the transition will take decades because the economic comparison will be between the long-run cost of alternatives to the short-run cost of existing energy sources. If together the political-economic inertia plus the transition adds another 50 years, then the damage to agricultural surplus could be catastrophic (Figs 6–8).

There are a number of reasons to believe that losses to U.S. agricultural surplus will occur sooner than indicated by the results, these reasons are given below.

IMPLICATIONS

Many economists conclude that we should delay implementation of any significant new policies to substantially slow emissions that cause global warming, arguing that we can always implement such policies later if related climate change proves to cause serious damage. They argue that, instead, we can adapt to warming and perhaps benefit from it; meanwhile, by putting off action, we may be able to avoid the cost of reducing emissions altogether, or at least delay the cost. The same economists argue that serious damage – if it occurs at all – will most likely occur in the agricultural sector, so I have focused here on that sector as a bellwether. This analysis introduces biogeophysical lags, formally represented by ocean thermal lags of a half-century. The evidence shows that the earth is now experiencing these lags (Levitus *et al*., 2000; Hansen, 1999). It is precisely because of such lags that comparative static economic analysis based on a doubling of CO_2 equivalent gases uses the wrong counterfactual. Cline (1992) developed this argument a decade ago, but most of the subsequent publications by economists have ignored this point.

Mendelsohn, Nordhaus and Shaw (1994) performed a comparative static analysis, estimating the difference between agriculture today as if a doubling of greenhouse gases occurred instantaneously **and** adaptation also instantaneously occurred, compared to agriculture today without climate change. The correct counterfactuals for comparative static analysis would be a future agriculture with climate change, compared to a future agriculture without climate change. We must expect that technological change would increase future agricultural surplus in the absence of climate change. Consequently, their comparative static analysis understates the losses from climate change. Improving on Mendelsohn, Nordhaus and Shaw (1994), Adams *et al*. (1999) perform the latter comparative static analysis, accounting for technological change that would occur in the absence of climate change. Comparative dynamic analysis is a further improvement because it can avoid arbitrarily selecting a doubling of greenhouse gases as the point for comparison.

To get the counterfactuals right, we need to specify the dynamic time paths with and without climate change. A comparative dynamic analysis considers the difference between the time paths for agricultural surplus both with and in the absence of climate change. In the absence of climate change we can expect future technological improvements. In the absence of significant policy intervention, climate change will continue until the economically available fossil fuels are gone. The correct time length for analysis, as Cline (1992) argues, extends until fossil fuels are no longer economic. The time path with climate change should include adaptation to climate change. Both time paths should incorporate technological change. But the technological change will differ between the two time paths. With climate change, there is the opportunity cost of diverting research and development to climate adaptation.

For a number of reasons, the forecasts with climate change in equations (23a–c) are optimistic. Some of the reasons are given in the literature.

Adams *et al*. (1990) acknowledge several critical omissions in their work and caution that their main contribution is "highlighting uncertainties" (p. 219). The GCMs do not "include changes in the space and time distributions of climate events. Therefore many significant climate and biophysical features are ignored." They further caution (p. 220) that they do not account for changes in climate variability, such as frequency of droughts, "mesoscale convection complex" rainfall, and hail damage. Adams *et al*. (this volume) consider these variations.

The forecasts in equations (23a–c) do not capture the impact of a long-term drought, which could be harsh, turning the interior Great Plains to desert. For water supply, as long as the annual constraint is not exceeded, the CSMs allow for the optimal amount of water to optimize crop growth over the growing season. Implicitly, the assumption is that the Army Corps of Engineers will build dams along the Mississippi river, canals throughout the Great Plains, and divert the headwaters of the Missouri river to the other side of the Great Divide to flow Southwest instead of going to the Mississippi. The forecasts do not capture the impact of torrential rains, stripping the land of topsoil. Nor do these forecasts capture the possibility that fluctuations between floods and droughts could amplify, both washing away the topsoil and baking into laterite (McNeil, 1964) what soil remains.

The crop simulation models assume no limits to soil nutrients, and no pests that limit crop growth. Adams *et al*. (1999) explain that the CSMs allow amounts of fertilizer to vary for optimal results, so the results do not admit damage to soil. The CSMs for corn, soybeans and wheat assume optimal pest management, and no nutritional limits in the soil that could limit CO_2 fertilization. See Erickson (1993) for a more complete set of reasons to be concerned that the forecasts with climate change are optimistic.

There is another reason, not noted in the literature, to be concerned. The forecasts in equations (23a–c) assume that technological change will continue into the future at rates equal to those of the past. McElwain, Beerling and Woodward (1999) examine the period at the Triassic-Jurassic Boundary when 90% of all plants became extinct. They estimate "that ambient CO_2 increased from 600 to 2100–2400 ppm across the T-J boundary" (p. 1387), so that RCO_2 equaled 2 and then increased until RCO_2 equaled between 7.5–8.5. Their estimate is consistent with the range of error in Berner's (1997) biogeological model (see Fig. 1). The forecasts presented above admit the possibility that technological change will allow us to survive an event that destroyed most life on the planet. What if such improvements are not possible? And even if they are, who would want to live in those conditions?

All three macro-models predict RCO_2 equal to 2 by 2075. The Reilly-Edmonds model predicts RCO_2 equals 8 before 2325. The Nordhaus-Yohe macro-model predicts this occurs before 2300. The Manne-Richels macro-model predicts this occurs before 2250. Technological change may be unable to meet this challenge. With a 50-year ocean thermal lag, to avoid the consequences the world economy would have to complete the transition to alternative energy sources at least a half century prior to RCO_2 equal to 8. Based upon the emissions forecast from the Manne-Richels model, we have to complete the transition within the 21st century. This begs the question, when do we have to begin implementing significant policies in order to complete the transition this century? Goodstein (this volume) explores some issues that affect the answer to that question, such as state dependency for technological change in the case of renewable energy sources.

The forecasts presented above are especially optimistic when comparisons are made between the impacts of global warming on U.S. agriculture and the developing countries. There are two important reasons. The first is that the U.S. has a greater ability to adapt. The expectation of adaptation in the U.S. is predicated on a continuation of the present government policy of subsidizing research and development. The world-view held by many economists is antagonistic to government intervention in the economy. Yet agriculture in the U.S. has the best possibility to adapt because of the Agricultural Experiment Stations and Extension Service. The institutional structure for adaptation in most of the developing parts of the world is minimal to non-existent.

NOTES

1. I thank Jane Hall and Richard Howarth for helpful comments on earlier drafts.

2. As discussed in the next section, in the DICE model by Nordhaus (1994) there is only one climate equilibrium, and all economic valuation of climate impacts occurs prior to any feedback effects in the model of heat re-emerging from the ocean.

3. For a definition, see Hall (1996).

4. The approximation is in Hall (1996); compare the tables there with those in Cline (1992).

5. E-folding time is for exponential decay what doubling time is for exponential growth. Suppose that a stock can be described over time by exponential decay to zero. At initial time, the amount is X_0 and over time the amount is given by $X_t = X_0 \exp(-rt)$. The time derivative is given by $dX/dt = -rX_t$. At $t = 1/r$, $X_t = X_0/e$ where e is the exponential number, approximately 2.71828. The ratio 1/e equals approximately 37%,

so the e-folding time is the time at which the stock falls by 63% of the original value X_0. For an annual decay rate, for example, if r equals 2%, the e-folding time is 50 years.

6. Nordhaus (1994, p. 40) states, "There is insufficient variation in the data (output from GCMs simulating warming from the pre-industrial period to 1990) to allow us to estimate more than two of the parameters, so we used physical data from the models to calibrate the two least important parameters." The "physical data" are based on a single number, the 500-years e-folding time for deep oceans (p. 37). Other physical parameters are values for the heat capacity of the top 133.5 meters of ocean plus land and air, and the heat capacity of the deep ocean, between 133.5 meters to 1500 meters in Norhaus' analysis. This is inconsistent with the historical record compiled and analyzed by Levitus *et al*. (2000). They show substantial changes in the surface to 300 meters, from 300 to 1000 meters, and from 1000 to 3000 meters, all interacting within a 50-year time scale. Obviously, the "two least important parameters" are important.

7. This sub-section is from Hall (1999).

8. Adams *et al*. use CSM models for which crop yields are hill-shaped with respect to climate variables. The producer and consumer surplus is derived from models in which producers maximize profit and consumers maximize utility. One would expect the results for the aggregate surplus to show theory-consistency. There is a well-known perversity for agriculture, however. When weather destroys yield, producer surplus may increase substantially because of inelastic demand. Another reason for testing hypotheses regarding the coefficients is that technological change varies across crops in the CSMs. Hypothesis testing helps to decide upon a specific version of the aggregate function that may reflect technological change in more than one fashion. This point is developed next.

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