Integrated Assessment Models

For Climate Change Control*

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1. Introduction

Climate change is one of the most fascinating and thoroughly studied environmental topics in the economics and scientific literature. The control of climate change is a formidable challenge: no other environmental problem has so much uncertainty, requires so much coordination among countries, and is so dynamically linked across time.

Climate change is so interesting because the problem encompasses all aspects of environmental science and economics. On the scientific side, significant uncertainties remain about the transport of the greenhouse gas (GHG) pollutants through the atmosphere and the effect of GHGs on the atmospheric temperature, ocean temperature, rainfall, and sea level. The study of such climate processes requires the use of large computer models called general circulation models (GCMs).

The economics of climate change is even less well-understood. Significant uncertainties remain about the impacts of climate change on industries such as agriculture and recreation (e.g., skiing). The costs of controlling a long-run problem like climate change depend primarily on the degree of technical innovation, which is obviously difficult to predict. For example, innovations in the automobile industry such as more inexpensive electric cars could dramatically reduce the seriousness of the climate change problem.[1] Assigning weight to benefits received far in the future is quite difficult. Finally implementation and credible enforcement of a climate change control policy across countries is a challenge for any regulation instrument.

1.1. Key Aspects of Integrated Assessment Models

On an individual level, many aspects of climate change are now under study in the literature. However, many researchers combine the scientific and economic aspects of climate change in order to assess policy options for climate change (as opposed to advancing knowledge for its own

[1] Because climate change is a long run problem, costs associated with slow adoption of new technologies such as fuel efficient cars are small.

sake). These models are known as integrated assessment models (IAMs). Examples include: Dowlatabadi and Morgan (1993, 1995), Kelly and Kolstad (1997a), Kolstad (1996), Lempert, Schlesinger, and Banks (1995), Manne, Mendelsohn, and Richels (1993, 1995), MIT (1994), Morita, et. al. (1994), Nordhaus (1994), and Peck and Teisberg (1992). IAMs are receiving increasing attention of late. The Intergovernmental Panel on Climate Change (IPCC), which in the past has focused primarily on the physics of climate change, has released a report on the socio-economic dimensions of climate change. The report includes a chapter which reviews IAMs (Weyant, et. al. 1996).

We define an integrated assessment model broadly as any model which combines scientific and socio-economic aspects of climate change primarily for the purpose of assessing policy options for climate change control. Other authors have similar definitions; for example Weyant, et. al. (1996) defines integrated assessment even more broadly as any model which draws on knowledge from research in multiple disciplines.

Weyant, et. al. (1996) give three purposes for integrated assessment: (1) assess climate change control policies, (2) constructively force multiple dimensions of the climate change problem into the same framework, and (3) quantify the relative importance of climate change in the context of other environmental and non-environmental problems facing mankind. An example of (1) is the assessment of an Intergovernmental Panel on Climate Change (IPCC, 1990 and IPCC, 1992) control policy on sea level rise and the resulting effects on coastal ecology or tourism. Another example of (1) is the computation of the optimal climate control policy. An example of (2) is ranking the importance of the temperature change from a doubling of CO_2 (the climate sensitivity parameter) and the discount rate parameter, which can only be done within an interdisciplinary framework. Another example of (2) is identifying the driving forces behind climate change by identifying to which sectors climate change is most sensitive. An example of (3) is ranking the benefits of climate change control with improving sanitation or improving medicine in developing countries. In Section 4, we show that IAMs have addressed all of these questions and have achieved specific results, although the degree to which policy makers have used the results of IAMs is open to question. Note that the Weyant, et. al. (1996) definition is particularly broad, which reflects the wide variety of uses for IAMs.

IAMs vary widely in several key areas. IAMs are divided into two broad categories, which vary according to the policy options available to the regulator (both GHG control policies and economic policies). IAMs also differ in the complexity of the economic and climate sectors. An important difference between IAMs is the treatment of uncertainty, a fundamental concern in climate change policy. Finally, IAMs differ in the responsiveness of agents within the model to climate change policies.

Policy evaluation IAMs (hereafter policy evaluation models) consider the effect of a single policy option (often one proposed in IPCC, 1990, 1992) on the biosphere, climate, and sometimes economic systems. Policy evaluation models are also known as simulation models. In contrast, policy optimization IAMs (hereafter policy optimization models) have a dual purpose: (a) to seek to find the optimal policy which trades off expected costs and benefits of climate change control (regulatory efficiency) or the policy which minimizes costs of achieving a particular goal (regulatory cost-effectiveness) and (b) to simulate the effect of an efficient level of carbon abatement on the world economy. The distinction between these two kinds of models is critical because the degree of complexity in the policy options dictates the degree of complexity in the IAM. Policy evaluation models consider a single exogenously specified policy and seek to estimate the effects of that policy on the environment. Policy optimization models search for the optimal policy, which is a complex process and computationally expensive. Hence, such models typically have economic and climate sectors which are relatively simple.

Policy optimization and evaluation models also differ on a deeper level. Policy optimization models invoke well-known theorems on the equivalence between an efficient solution and the market equilibrium with an internalized public good provision.[2] That is, policy optimization models find the same level of GHG control we expect to observe in a government elected by rational voters, and the same responses we expect to observe from rational agents. Policy

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[2] Indeed, many policy optimization models start with a market economy in which the regulatory instrument is a tax and then convert the model to an equivalent problem which finds the optimal emissions (see, for example, Nordhaus and Yang, 1996). Such models maximize a weighted sum of utilities where the weights are adjusted until individual budgets balance, which is equivalent to a Pareto optimum by the second welfare theorem. Other policy optimization models start with optimal emissions and convert the results into a tax.

optimization models are thus normative and provide a description of the world, given the assumptions of the equivalence theorems. Policy evaluation models take actions by agents and governments as given, provided by policy proposals, assumption, observation, and/or expert opinion. Policy evaluation models thus have more freedom to model phenomena that are inconsistent with some of the assumptions of policy optimization models. For example, in a policy optimization model implicitly assumes optimal economic growth rates (and therefore future emissions), which are higher than has been observed in some developing countries.[3] A policy evaluation model is free to assume that growth in the developing world matches the historically observed growth rates. A policy evaluation model is, however, only as good as the modeler's ability to predict decisions. A reader thus cannot readily interpret why agents respond the way they do in policy evaluation models (i.e. why economic growth is so slow in some countries). Thus, policy evaluation models are more like "black boxes" and the meaning of the results is less clear.

The advantage of policy evaluation models versus policy optimization models is that policy evaluation models allow for much greater detail on the physical, economic and social aspects of the very complex climate change problem. However, added complexity is usually a mixed blessing since what drives the results in complex models is rarely clear. Conversely, optimization models have complex policies which can depend on state variables such as the state of the climate and economic growth. Further, optimization models allow for economic responses to policies. An optimization model may let producers and consumers determine endogenously the optimal mix of GHG intensive and non-GHG intensive fuels given a climate change control policy, while in an evaluation model the modeler specifies exogenously the mix of fuels used. Hence policy evaluation models must rely essentially on the skill of the modeler in taking into account how consumers and producers behave. However, optimization models lack detail and abstract away from what some consider important details in climate change.

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[3] Usual reasons for slow growth are differences in variables such as education and life expectancy (see for example, Summers and Heston, 1991) and differences in economic institutions and structure (see for example, Mauro, 1995 or North 1996). Such complications are not included in any policy optimization model.

Within the policy evaluation or optimization model types, significant variation exists in the level of complexity of the economic and climate sectors. Some IAMs (both optimization and evaluation) are geographically complex and divide the world into as many as 19 regions, each differing in emissions and impacts. Other models have a highly complex energy sector that forecasts conversions to alternative energy technologies as the cost of fuels which emit GHGs rise. On the physical side, some models based on GCMs model the climate with great care and account for variations in climate change across different types of topography, while others have a complex model of atmospheric chemistry, allowing for many different types of GHGs. As pointed out in Tol, et. al. (1995), there does not appear to be any consensus about what aspects of the climate change problem should be included in an IAM model. For example, Weyant et. al. (1996) states that "IAMs should consider the problem of local air quality," because changes in weather affect the removal of local air pollutants. Modeling changes in local air quality would add enormous complexity. Why local air quality is more important than other un-modeled aspects of climate change that could be added (with perhaps less complexity) is not clear.

Many IAMs are designed to answer smaller questions about climate change. For example, if a researcher is interested in the degree of technical change that can be expected to arise from an aggressive control strategy, a policy evaluation model with a highly complex energy sector may be appropriate. But in most models it is not clear why some aspects of climate change are included and others are not. Tol, et. al. (1995) proposes that IAM models should be "balanced." That is, IAMs should pay relatively equal attention to the various components of the climate change problem.

Another idea is to model those aspects of climate change for which the optimal or best climate change policy is most sensitive. For example, if climate change control rates are very sensitive to the inclusion of sulfur dioxide (which is discharged from burning coal and acts to cool the earth), then the case for including sulfur dioxide in IAMs is strong. If an IAM finds similar control rates when sulfur dioxide is integrated with other GHGs into a single pollutant, then modeling sulfur dioxide separately needlessly adds complexity. A problem with this approach is that few studies actually compute for what aspects of climate change the control policy is most sensitive. A study might vary some parameters of the model and compute how the results change, but few studies compute how the results change if another sector or another GHG or another region is added. A few new results in this area, detailed below, indicate the importance of economic growth assumptions and the role of discounting. Few IAMs have a complex model of how economic growth occurs and fewer still have a complex model of discounting (through, for example, an overlapping generations framework).

An important feature of some policy optimization models is allowing agents to respond to GHG control policies. For example, a policy evaluation model might take as exogenous a forecast of uncontrolled emissions growth over the next century, and then evaluate the impact of a proposed IPCC control policy and compare the impacts to those that occur with no control policy. However, emissions growth projections are based on economic growth. Economic growth will be quite different in a world with a restrictive control policies versus a world with no control policies (due to the response of economic agents to the GHG control policy). Hence uncontrolled emissions are quite different, which violates the implicit assumption that uncontrolled emissions do not vary. All policy evaluation models and even some policy optimization models let uncontrolled emissions be exogenous, although a few fully specified policy optimization models take into account such changes in behavior. Modeling uncontrolled emissions has important consequences. For example, Manne and Richels (1993) show that if consumers believe the chance that emissions will be reduced to 1990 levels in 2010 is 50%, consumers will reduce emissions in the year 2000 as if a tax of $17.50 per ton of carbon were already in place.

1.2. Uncertainty in Integrated Assessment

One of the dominant issues in the economics of climate change is the role of uncertainty. Manne and Richels (1992), in their important book on controlling precursors of climate change, focus almost entirely on hedging against uncertainty. Nordhaus (1994), in his equally important book on the economics of climate change, devotes considerable space to the implications of uncertainty for forming control policies.[4] The policy debate world-wide is dominated by the

[4] Other papers that have considered these issues include Hammitt et al. (1992), Kolstad (1993), and Peck et al. (1989).

question: "Do we know enough to control the problem now or should we wait until more is known about climate change?" Although uncertainty is always present in problems of environmental policy, the uncertainty is much greater in the case of climate change if for no other reason than the problem and its solution span decades or even centuries. Implicit in the decision about controlling now or waiting is how fast uncertainty is resolved. If research resolved uncertainty quickly (as is currently predicted), then waiting until more is known costs little. If uncertainty is not resolved quickly, then costs associated with waiting can add up.

The uncertainty problem has two dimensions: parametric uncertainty and stochasticity. Some aspects of climate change are not well understood, although presumably over time the problem will be better understood. We are uncertain about particular parameters of the problem, but we expect that uncertainty to diminish with time or effort (e.g., R&D). We might also be concerned with the structure of the problem. These are examples of what we term parametric uncertainty.

A close relative of parametric uncertainty is stochasticity. Stochasticity arises from phenomena that affect the economic or physical processes, but are not modeled. First, regardless of how complex an economic or physical model is, some elements are inevitably not modeled. Often the sum of the not modeled parts of a process behave like a stochastic shock. For example, volcanoes, sunspots, and hundreds of other phenomena affect the global mean temperature in a way that is approximated by an AR(1) process (see Kelly, Kolstad, Schlesinger, and Androva, 1998). Secondly, one cannot know the future values of many economic and technology processes because if the future were known, consumers would act on that knowledge in ways which change the future. For example, future economic growth rates (and hence emissions) are stochastic because if an IAM could predict future values of GDP, consumers and investors could use the same model to predict GDP and use the results to change savings and consumption behavior. Here a random walk approximates the stochastic GDP process quite well. Hence climate change is subject to stochastic shocks which affect climate, technology and costs; but the future values of these shocks are always uncertain. These two elements--parametric uncertainty and stochasticity-

-generate significant uncertainty in trying to formulate policy for controlling greenhouse gases (GHGs).

To make things more complex, parametric uncertainty is not constant over time; that is, learning takes place. Over time, learning can reduce parametric uncertainty. By investing in R&D, or observing climate behavior, we can learn about uncertain parameters. Of course, *ex ante*, we do not know how parametric uncertainty will be resolved.

Learning has many dimensions. Learning can take place at various levels of a policy problem, ranging from agents in the economy who are learning in order to adapt to changes in their environment to policy-makers who are trying to formulate the best policy in an uncertain and changing world. When agents within the economy react to changed circumstances, it is usually termed adaptation. If these agents perceive uncertainty but learn over time, then adaptation takes time. While learning is taking place agents adjust, making suboptimal decisions (relative to perfect information) with resulting welfare losses. To offer an overly simplistic example, suppose the climate has changed in the Midwestern US, resulting in a higher frequency of flooding and more rainfall. It may take decades before farmers realize the change is permanent and combat the increased rainfall by changing the crops (perhaps planting flood resistant strains). In the meantime, significant crop losses occur. Even if farmers could adapt perfectly to the changed climate, the delay in realizing a change has occurred results in significant losses.

Policy-makers also base decisions on some body of knowledge. When that knowledge base evolves over time, regulatory decisions evolve over time. More subtly, current regulatory decisions must take into account the fact that more will be known tomorrow. This process takes time and the decisions made in the interim influence the rate at which information is being acquired.

In addition to who learns, we can characterize how learning occurs.[5] Passive learning involves the exogenous arrival of information. This may occur all at once, as in Manne and Richels (1992), or more gradually as a function of time, as in Kolstad (1993, 1996). Obviously

[5] See Cunha-e-sa (1994) and Kolstad (1996) for further discussion of different types of learning.

there has to be some process whereby information is generated and arrives; however, with passive learning, that process is exogenous to the system being examined.

We let active learning denote learning where agents have some influence over the rate at which information arrives. For instance, investment in research and development (R&D) yields information. R&D is an obvious way in which information is acquired and a clear example of active learning. It is also a major factor in learning about climate change.

Learning from experience is a form of active learning which is also very important in climate change. If a monopolist is uncertain about a demand curve, she can experiment by varying price and observing sales, learning over time about demand (Balvers and Cosimano, 1990). We could interpret our climate change policy as a grand experiment: by increasing GHG emissions we obtain information about how emissions influence the climate.

In the example of the farmer learning from realizations of the climate, learning occurs without R&D, simply by observation. Furthermore, much effort has been expended by the research community in trying to detect a climate change footprint/fingerprint in the temperature record of the last century. For example, Schlesinger and Ramankutty (1995) and Bassett (1992) examine the statistical properties of the relationship between global mean temperature and greenhouse gas concentrations. Researchers also search for signs of climate change in ice core and tree ring data (for example, see Folland, Karl, and Vinnikov, 1990). Both types of learning are necessary to conclude the climate is changing. The laboratory offers a controlled environment which isolates the problem. Observation confirms that the problem remains in the uncontrolled environment. If a signal is clearly evident, a much stronger case can be made for controlling the problem.

Uncertainty poses special challenges from the point of view of IAMs. IAMs are already typically complex, and *explicitly* modeling uncertainty (i.e. the decision maker or planner makes climate change control decisions without perfect knowledge of some parameters or variables) adds significantly to the complexity since the decision maker must consider each possible resolution of uncertainty. Explicitly modeling learning also adds significant complexity.

Because of the complexity, most IAMs treat uncertainty more simply via sensitivity analysis in various forms. The most common treatment is a type of Monte Carlo analysis known as *stochastic simulation* (Weyant, et. al. 1995). Suppose uncertainty exists over a vector of parameters. Stochastic simulation is a technique which simulates the model under various parameter values. First a random draw is made from a given distribution over the uncertain vector. Then the modeler finds the results of the IAM under certainty for the randomly drawn parameter vector. Then another vector is drawn and the modeler again computes the results of the IAM. After a large number of draws, the average result becomes a measure of how the IAM might perform under uncertainty. This method has a particular advantage in that several uncertainties considered together may have a compound effect on the IAM results. Models which do sensitivity analysis one parameter at a time under estimate the effect of uncertainty because such compound effects are in effect ignored.

Under a special case known as certainty equivalence, stochastic simulation correctly gives the optimal action under uncertainty. Certainty equivalence occurs when the optimal action under uncertainty is equivalent to the expected value of the actions under each realization of the uncertain parameters with certainty. However, because of risk aversion certainty equivalence does not hold in climate change models. Furthermore, stochastic simulation offers no model of learning, or how uncertainty might be resolved over time. All uncertainty is (unrealistically) resolved immediately. Decisions cannot be made based on the results of learning and the relationship between learning and GHG control policies is unclear.

The problems with stochastic simulation has led a few modelers to consider a model where the decisions are actually made under uncertainty, such as Peck, Chao, and Teisberg (1989). Due to the complexity of decision making under uncertainty, such IAMs consider only limited forms of uncertainty. Most of these models consider only discrete uncertainty with passive learning. Discrete uncertainty modeling usually consists of a single uncertain parameter, which can take on one of two possibilities with some probability. Uncertainty is resolved at a fixed time in the future, and hence learning is passive. Such models can compute the value of information, or the difference in discounted consumption between the model under certainty and under uncertainty. Most modelers find the value of information is small. This result is, however, sensitive to when uncertainty is resolved, which is itself uncertain (Peck, Chao, and Teisberg, 1989). Furthermore, total climate change damages are themselves small relative to the gross world product,[6] so it is not clear if the value of information is small relative to the total costs of climate change.

Discrete uncertainty does not assume certainty equivalence and hence gives the optimal policy under uncertainty (although the assumption that a single parameter takes on only one two values understates the true uncertainty policy makers face). Further, discrete uncertainty allows information to change over time and hence gives an idea about how decisions relate to learning. However, because learning is passive, learning is unaffected by control policies. Kelly and Kolstad (forthcoming) model active learning by observation and determine that uncertainty is resolved after 90-160 years, far longer than assumed in most passive learning models. Further, when uncertainty is resolved is determined in part by GHG control policies. For example, restrictive GHG control policies such as those proposed by the IPCC slow learning considerably. Kelly and Kolstad (forthcoming) also find that optimal control policies are quite sensitive to learning, which gives an indication of the value of learning relative to total climate damages.

1.3. Review of Integrated Assessment Models

Table I gives a list of IAMs and how IAMs vary in the above dimensions. Of the 21 IAMs analyzed, ten are evaluation and 11 are optimization, suggesting no consensus exists on what type of IAM is best. Table I also shows that of the 21 IAMs analyzed, only one third allow any economic response to policy, and only five allow for more than one type of economic response. Those models that allow economic response to policy typically allow agents to vary the consumption/investment decision. This arises naturally out of the optimal growth framework, which all of these models use. Within the optimal growth model class, many IAMs have a production technology which specifies energy usage (either GHG intensive energy or non-GHG intensive energy) as an input. Hence producers may respond to GHG control policies by reducing GHG intensive energy usage, by either conservation by using more capital and labor or by using more non-GHG intensive energy. IAMs still have only very limited economic responses,

[6] For example, Nordhaus (1994) estimates a three degree Celcius tempertaure rise (which occurs long after uncertainty is resolved) reduces gross world product by 1.33%. Mendelsohn,

however. For example, none of the models we have seen model adaptation or technological change endogenously.

Table I also shows the differences in complexity across policy evaluation and policy optimization models. Our definition of complexity in each category is not very restrictive. The only requirement for a complex model of atmospheric chemistry is a separate model of at least two GHGs (for example CO2 and sulfur dioxide). A complex climate has an explicit model of more than two climate layers or regions (for example temperature change in northern and southern hemispheres or a seven layer climate model) or explicitly models more than one climate change effect (such as rainfall or sea level rise). A complex economic model has an explicit energy sector or a complex model of impacts across regions or industries. In spite of our relatively weak definition of complexity, no policy optimization model has a complex model of atmospheric chemistry, none have a detailed climate, and few have a detailed economy. Conversely, many policy evaluation models have both a complex atmospheric chemistry model and a complex climate model. Indeed, two of the ten policy evaluation models have a complex climate, chemistry, and economic model.

Table I also shows the wide range of treatments of uncertainty. A majority (seven) use the stochastic simulation method described earlier, which allows multiple parameters to vary simultaneously from a joint distribution, but still assumes certainty equivalence. Five models allow for a limited form of actual decision making under uncertainty, where the uncertainty is discrete and resolved at a specific time in the future. Many models still have no formal treatment of uncertainty. Only one model allows for continuous decision making under uncertainty where resolution of uncertainty is endogenous and that model allows for only one uncertain parameter.

2. Critical Assumptions of IAM models.

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et. al. (1996) estimates a 3 degree temperature rise to be approximately neutral on the United States economy.

Like all models, results from IAMs are driven by the critical assumptions of the models. A few of the assumptions of IAMs have received some attention in the literature, especially the debate over the appropriate rate of time discount. But for the most part, discussion of critical assumptions is noticeably lacking. However, a number of critical assumptions have been identified, which for the most part drive the results that are common to all IAM models.

2.1. Discounting

Perhaps the most often debated critical parameter is the rate of time discount (for example, see Arrow, et. al., 1996, Cline, 1992, and Nordhaus, 1994). Most of the benefits of climate change control (or the costs of climate change) are derived far in the future. Hence the more weight that is placed on the future, the more optimal climate change control rates rise. The discount rate is critical since small changes in the yearly discount rate compound over decades and centuries. Indeed in models which allow for economic response to policy, if a low rate of time discount is used, investment rates are higher and hence growth is higher and hence uncontrolled emissions are higher, which further increases the optimal control rates.

In infinite horizon models such as IAMs, several parameters determine the rate of time discount. The first parameter is the pure rate of time preference. The pure rate of time preference is where IAMs differ. The second parameter is the weight assigned to future generations. Most IAM models weight future generations equal to the present generation (except through the pure rate of time preference). A final parameter which affects the rate of time discount is the economic growth rate, along with the concavity of the utility function. Future generations are inherently better off because per-capita economic growth is generally rising due to advances in technology. Because marginal utility is declining, benefits to more wealthy future generations are less socially beneficial than benefits given to the current generation. The social rate of time preference is thus equal to pure rate of time preference plus the the economic growth rate times the elasticity of marginal utility. IAMs range from Cline (1992), where the pure rate of time preference is set to zero (based on equity considerations), the economic growth rate is 1.6%, and the elasticity of marginal utility is 1.5, which would give gives a social rate of time preference of about 2.4%. Other models calibrate rates of time preference by observing real world interest rates. Calibrated models find a pure rate of time preference as high as 5%, which along with a 1.5% growth rate implies a social rate of time preference of 8%. The same IAM model with these two discount rates yield quite different results, especially in the future. Cline (1992) finds an optimal control rate as high as 50% by 2100, while Nordhaus finds an optimal control rate of only 13%. One problem with rates of time preference set via equity considerations is that the results of such models are difficult to sell to the developed world. In effect, such models say that the developed world must make sacrifices for the benefit of future generations in countries with high population growth rates such as China and India. Such models usually give investment rates far in excess of that which is observed, which leads to unrealistically high forecasts of uncontrolled emissions. However, calibrated models have been criticized based on the use of observed interest rates, which do not in general equal the pure rate of time preference because of distortions from non-optimal tax rates and because some environmental goods are not traded and not included in national accounts.

An early related technical issue was the appropriate terminal period to use in numerical calculations. Cline (1992, pg. 309) argued that the inclusion of very long term time horizons (and thus long term warming) generated significantly higher control rates compared with other researchers such as Nordhaus. However, in fact researchers such as Nordhaus (1994) actually used very long time horizons of 600 years, but simply did not report control rates beyond the year 2100 because the results were "too conjectural." Indeed, Nordhaus (1991) shows clearly that the higher control rates obtained by Cline are due soley to the low rate of time preference. This is further supported by Nordhaus (1994), which shows that his model is not sensitive to the choice of terminal period (beyond 400 years), and by Kelly and Kolstad (forthcoming) who use an infinite horizon model and get similar results.

2.2. Economic Growth

The second most critical assumption is the assumed amount of economic growth in GHG intensive industries. Most IAMs tie GHG emissions to industrial production either implicitly through emissions projections, which are based on the growth in industrial production or explicitly through an actual model of industrial production. Economic growth results directly from advances in technology and population growth, and from a high marginal product of capital in the developing world. As demonstrated in Kelly and Kolstad (1996), without growth in population and advances in technology, there will not be enough emissions to drive any climate change (much beyond that which has already occurred). Similarly, scenarios with high growth consistently find considerably more climate change and hence more spending on climate change control. This is readily apparent in the 1990s, where high growth around the world has produced higher than expected emissions of GHGs across the world. In fact, IAMs are usually quite pessimistic in their assumptions about the growth rate of production and hence emissions. A survey from Nordhaus and Yohe (1983) reveals that most IAMs assume a large slowdown in technology growth over the next century (primarily to make the problem computationally tractable). Similarly, most IAMs take population growth numbers from the United Nations (1994) or World Bank (1991) studies which predict zero population growth by the year 2200. Hence projected emissions growth also slows down and ends by the year 2200.

2.3. Economic Response to Control Policy

A third important assumption is when and where economic agents are able to respond to emission reduction policies. History is full of IAMs in other fields which made poor predictions, because the models did not allow for the response of economic agents to policy. For example, consider the limits to growth debate of the 1970s (see Meadows, 1972). These models made dire (and yet-to-be-realized) predictions about the effect of growth on the environment and natural resources, because they did not take into account the economic response of rising prices, substitution, and innovation to scarcity.

By “economic response” we mean here an *endogenous* response, that is an agent makes a decision optimally given a control policy. Many IAMs have *exogenous* built-in responses by agents, such as an exogenous change in fuel usage at a specific energy price. However, an exogenous response cannot easily capture the complex relationships that go into an endogenous decision. For example, suppose an IAM modeler perfectly specifies (exogenously) usage of solar energy as the price of fossil fuels rise. Now suppose that sensitivity analysis is performed with a parameter change that results in higher economic growth. Then the relationship between the price of fossil fuel and the usage of solar energy changes, because incomes and other factors which affect demand change. But since the response is exogenously fixed, the relationship is incorrect, even though the relationship between fuel usage and prices was designed perfectly for the base case.

An IAM cannot possibly include all economic responses, because each possible type of economic response is really an extra decision variable, which adds significant complexity and computational cost. Therefore IAMs tend to differ in how and when (if at all) agents can respond to policy, which is an important factor in interpreting the results of IAMs. A variety of possible responses exist, from the adoption and/or development of cleaner energy technology to changes in consumption and investment.

The most common type of economic response is the ability of agents to change investment decisions in the face of GHG control policies. For example, agents may compensate for an overly restrictive GHG control policy. Suppose the world economy is in equilibrium and a restrictive control policy is put in place (ie a control policy which is more restrictive than the optimal policy). A restrictive policy is paid out of current income, which invariably results in a reduction in both consumption and investment. Lower investment implies lower future capital stocks and hence lower uncontrolled emissions.

Another common economic response in many IAMs is the ability of producers to reduce usage of GHG intensive fuels as the price rises. Producers may compensate for higher GHG intensive fuel prices by using non-GHG intensive fuels (ie natural gas, wind, or solar), or by using more capital and labor in the production process.

Although a few IAMs allow for investment and energy responses, other economic responses are much more rare in IAMs. For example, economic agents clearly act to mitigate climate change damages and costs. Some IAMs allow for more convex damages when climate change is abrupt (implicitly assuming climate change is unexpected), but such a response is fixed and not endogenous. A more general model would allow for adaptation based on expected climate change.

A final critical assumption is the degree of aggregation. Many models have but one or two regions of the world and find the optimal world GHG emissions level, but do not address how countries would share the burden. Those models that do divide the world regionally are better able to assess the benefits and costs of climate change control across regions. However, such models must take into account the puzzle of designing enforceable international agreements. In an international agreement on climate change each country has a relatively small impact on the total world emissions, hence the incentive to cheat is strong.

2.4. Long Term Forecasting

How important is projecting/predicting the future accurately for integrated assessment? Some say that the purpose of an integrated assessment model is to pull together the diverse strands of understanding about a problem to generate the best prediction possible about what the future may bring or about the future effects of a specific policy. However, the quest for accuracy often breeds complexity. And complexity breeds opaqueness which for an IAM can mean uselessness.

At the other end of the spectrum are the small models of climate change that seek to capture the essence of the climate change process without adding complexity. Nordhaus (1994) fits into this category. With such a simple structure, it is possible to communicate the model's operation to others and for others to learn from its use. This is one reason why the model of Nordhaus (1994) has been used by many other analysts as a starting point. The problem with the more simplified approach is that simplified models may be too simple to be useful for policy-making. For instance, the original Nordhaus model aggregates the world into one large region and simulates the economy with three equations. This is the essence of economic modeling—strip away unnecessary detail and focus on the core structure of the problem. We learn from this exercise but cannot place any "faith" in the numerical results that emerge from the model, at least as a basis for policy. Manne, Mendelsohn, and Richels (1993) are mid-way between simplicity and complexity in the Merge model and its progeny. Manne, Mendelsohn, and Richels (1993) have a structurally simple economic sector with significant detail on the energy sector. Despite this, some consider their model structure overly simple as a basis for policy.

Thus tension between detail/realism and simplicity/transparency characterize IAMs. Finding the right balance between these two conflicting goals is difficult. Given the purpose of IAMs – to educate rather than predict – our preference is to err on the side of transparency and simplicity, at the expense of precision and accuracy. That is the essence of abstraction – to focus in on the core operation of a system and learn from the resulting simplified model.

3. Main Results of IAM Models.

IAMs share many common results and tend to agree more than disagree. The modeling community have also taken unprecedented steps to compare and contrast results in settings such as the Energy Modeling Forum (see for example EMF, 1993). This has even led to some "model convergence," whereby initially diverse model predictions have converged over time. A number of significant results have come out of IAMs.

Perhaps the most surprising result is the consensus that given calibrated interest rates and low future economic growth, modest controls are generally optimal. This was the key result of Nordhaus (1994), which has now been found by many modelers. Generally results are in the range of a 5-10% reduction in emissions versus no control. This corresponds roughly to a tax of $5-10 per ton of carbon. Hence most models find that only a modest slowing *of the rate of increase* in emissions is warranted. This contrasts visibly with proposed policy measures of the IPCC and the Protocol conference which are in the range of 5-10% *below 1990 levels*. Still, 5-10% emissions control is significantly tighter than the current policy of no control.

The result on modest controls comes primarily from the critical assumptions listed above. First, since economic growth is modest, especially in the next century, emissions growth is modest and therefore the need for GHG control is modest. The result is also sensitive to the assumptions in the discount rate. If a zero rate of time preference is used, control rates are substantially higher. Finally, substantial exogenous innovations in the energy sector are built into most IAMs. If the true economic response is such that improvements do not arrive, or arrive more quickly than expected, the results would differ substantially.

The discordance between the results of IAMs and the currently proposed policy options raises important questions about the purpose of integrated assessment. IAMs seem to have answered two major questions, the role of climate change in context of other problems and the assessment of optimal and other climate change control policies. However, the influence of these two major results on the policy debate is open to question. The Kyoto and IPCC policies are more restrictive than most IAMs. Perhaps policy makers are guided by political agendas or are unable to trust the "black-box" nature of IAM results (that is, in many IAMs it is not clear what assumptions drive the model). For example, the year 1990 is critical to politically-minded policy makers, but not to IAMs. In 1990 the former East Germany's outdated factories were emitting very high levels of many pollutants. Thus to reduce emissions below 1990 levels, Germany needs only to replace the outdated factories, something that would have been done anyway. Modelers must take a more active role in the policy debate and bring the results to the forefront of the policy debate. Similarly, modelers must do more to explain what drives IAMs, which makes the results more understandable and trustworthy.

A related area of study is the optimal timing of GHG control policies. One possible control strategy is to act now, and institute a control policy immediately. Acting now hedges against unknown, but possibly severe, future damages. A second option is to wait-and-see, deferring action until more is known about the problem. Several results have emerged in comparing these two policies. First, IAMs which calculate the optimal GHG control level generally find some small immediate reduction in emissions is warranted. However, the cost of delaying control for a decade or two is quite small and the heaviest reductions are in the later years (see for example Richels and Edmonds, 1995 and Manne and Richels, 1992 and 1993). These results tend to advocate acting now, but again in a modest way. Results by Kelly et al (1998) also show little resolution in uncertainty in the next decade, which make the informational gains from waiting small. Finally, such results are sensitive to assumptions about technological innovation and the speed at which new capital is adopted.

As we have noted, from the early debates between Cline (1992) and Nordhaus (1994), most IAMs find that one critical parameter is the discount rate. This has generated some research in the environmental economics area which tries to better pin down the appropriate discount rate (see for example, Laibson, 1996, Lind, 1994, Manne, 1996, Schelling, 1995, Weitzman, 1994, and Weitzman, 1997). For example, Weitzman (1997) shows that if uncertainty over the rate of return to capital in the distant future exists, then the lowest possible interest rate (and hence the discount rate which is closest to one) that occurs with positive probability should be used for discounting. This occurs because eventually the present value of all other possible outcomes becomes small relative to the lowest-interest rate outcome. Manne (1996) compares the overlapping generations framework with the more standard infinitely lived agent framework. The overlapping generations model allows for more transparent modeling of bequests and other important aspects of long term discounting. Manne (1996) finds that there is an overlapping generations model and an infinite horizon model yield similar results when the consumption (not utility) discount rates are equal. Laibson (1996) considers hyperbolic discount rates (the psychology literature gives some evidence of hyperbolic discounting, see Laibson, 1996), which leads to under saving, and hence in an IAM would lead to under-investment in GHG control.

Another useful result is the evaluation of proposed policy scenarios, such as the IPCC scenarios. The IPCC (Watson, et. al. 1990) has proposed 5 scenarios for GHG emissions over the next century (including scenario "A", which corresponds to business-as-usual). These scenarios differ quite widely: The business-as-usual case results in a CO_2 concentration nearly twice as high as the most aggressive control scenario by 2100. Other proposed policies focus on stabilizing emissions at 0-10% below 1990 levels at some point in the future.

IAMs show that such policies result in drastically different outcomes. In Nordhaus (1994) the present discounted difference between the optimal policy and immediate stabilization at 1990 emissions levels is about 12 trillion 1989 dollars. Manne and Richels (1997) examine a variety of emissions scenarios and evaluate the economic costs. Costs can range from as little as $.5 trillion for the least-cost trajectory to as high as $8-9 trillion.

4. Directions for Research.

Most integrated assessment models are now quite complicated, with explicit models of many features of the climate and economic systems. Still, a number of under-studied areas deserve attention. Many of these areas are now currently under study.

4.1. Endogenous Technical Change

An elusive, but essential, aspect of the climate change problem is technical change. Technical change may be both emissions increasing: improvements in productivity leads to economic growth, or emissions decreasing: improvements primarily in the energy sector (improved energy efficiency or improvements in non-GHG intensive fuels) lead to less emissions per unit of production or consumption. Productivity-enhancing technical change in the 1990s has led to economic growth, which has substantially increased emissions. Estimates for economic growth in most models are quite low relative to historical observations. Still, most models recognize the importance of this kind of technical change and at least consider high growth in sensitivity analysis.

Technical change in the energy sector is more problematic for IAMs. Technical change has the possibility of being critically important. For example, innovations such as inexpensive electric automobiles or solar power has the potential to significantly change the threat of climate change without any regulation. Since climate change is a long run problem, innovations have plenty of time to penetrate the market. Of course such innovations are unpredictable, but at least some innovation seems quite likely.

Previously, modeling of technical change has been exogenous. One way to get an exogenous estimate of the degree of technical change is to examine the historical record. The CO_2 emissions intensity of output has fallen world-wide from 0.409 tons of carbon per thousand dollars of output in 1929 to 0.232 tons/$1000 in 1989 (Nordhaus, 1994). This includes substantial increases in the intensity of output in the former USSR and China. Nordhaus calculates an improvement in emissions intensity of about 1-1.5% per year. Some IAMs simply assume that further improvements occur at a similar, but declining rate of change as that observed in the past.

The other way to get an exogenous estimate of technical change is to build a model of energy usage where shifts in energy technology occur at specific energy prices. As energy prices rise from regulation, usage of GHG-emitting energy declines. Such models also often have a "back-stop" technology whereby at a certain energy price a GHG-free energy source becomes cost-efficient. Manne, Mendelsohn, and Richels (1993) have a particularly detailed model of the energy sector. The model has an exogenous rate of improvement in emissions intensity of about 0.5% per year. Further, capital, labor, and energy form a constant returns to scale, constant elasticity of substitution production function. Hence producers may substitute some capital and labor for energy if energy costs are high. Producers may choose between many different energy technologies which have different costs and GHG emissions properties. Some carbon-free technologies become feasible only at specified dates in the future. In spite of the complexity of the model, innovation is exogenous. The set of alternative technologies is fixed and exogenous and becomes available at fixed and exogenous times and prices.

Such models do not take into account endogenous innovation. As prices rise and regulation becomes more stringent, firms may spend more on innovation to attempt to reduce emissions costs. In fact, one of the more attractive features of emissions taxes and tradable permits is that such regulation instruments spur innovation. Indeed Goulder and Schneider (1996) find theoretically that the costs of achieving a specific abatement target falls when endogenous technical change is included. However, researchers are still struggling with numerous aspects of endogenous technical change. First, considerable uncertainty exists over "knowledge spillovers," or the degree to which other energy producing firms can use innovations from another firm. Another important distinction is the degree of previous distortion in the R&D market. Since R&D is a positive externality research should be supported via subsidies or patent rights. However, it is unclear how close we are to the optimal level of R&D spending. Further, other forms of innovation, such as learning-by-doing, have yet to be examined within the climate change framework.

4.2. Specifying Regulation Instruments

As described in Fisher et. al. (1996), policy makers have a wide variety of regulation instruments to use for climate change control. These include well-known regulatory instruments of taxes, command-and-control methods, and tradable permits. Many complimentary regulation instruments also control climate change: R&D subsidies, population control, taxes on gasoline, subsidizing energy which is not GHG intensive, subsidizing adaptation (by encouraging replacement of outdated equipment), and subsidizing reforestation all can potentially reduce GHG emissions. IAMs, on the other hand, generally consider only one of two policy instruments. Most IAMs calculate only the optimal or prescribed GHG emissions target, and then convert the optimal emissions target into an optimal tax on carbon, by calculating the tax needed to achieve the specified emissions. Other IAMs model the tax on carbon directly, then construct a social planning problem. Such models miss important features of many regulation instruments, however.

Consider first revenue recycling provided by taxes and permits which are sold. In many proposed policies by the IPCC, carbon taxes will likely be quite high, leading to significant revenues which can be used to offset distortionary income taxes. Even in models which compute the optimal tax, (although probably not fully, according to Goulder, 1995). Revenue recycling has yet to be included in most IAMs.

Another challenge is creating a regulation instrument which is usable internationally. Since each country is sovereign, therefore incentives for each country not to comply with optimal GHG reduction numbers are strong. Within a country, a carbon tax (unlike complementary regulation instruments such as gasoline taxes) is difficult to collect and monitor. Carbon dioxide emission occur both through gasoline consumption and through electricity production, as well as a host of other means. Each emissions source would likely require a different taxation and monitoring scheme. Hence any regulation instrument should include monitoring and penalties for non-compliance, which increase the costs of regulation.

Finally, inefficient regulations can increase adaptation costs. For example, farm subsidies and subsidies to flood-prone areas add significantly to the adaptation costs of climate change. In general, by examining only the optimal or proposed emission targets, IAMs miss important costs and benefits of climate change regulation. Further, incorporation of actual policies improves the usefulness of IAMs for policy making, as such a model gives not only a target, but a way of achieving the target.

4.3. Adjustment Costs and Damages

Perhaps the most important, but not yet modeled, economic response is adaptation. Agents within the economy respond not only to policies, but to climate change itself, irrespective of the existence of regulation. For example, given changes in temperature and rainfall, farmers modify input decisions such as irrigation and crop choice in order to lessen the impact of climate change. Such adaptation occurs regardless of the climate change policy.

Of course for adaptation to occur, economic agents must know exactly how the climate has changed. If climate change is uncertain (as it now is) adaptation is more difficult. In a world of imperfect information about climate change, damages are greater due to imperfect adaptation.

Many studies which estimate the damage from climate change assume complete information and perfect adaptation. Such models find relatively little damage from climate change (Mendelsohn, et. al., 1994). Most of the damage occurs on the adjustment path. This could be incorporated into an IAM by making damages greater under uncertainty. When uncertainty is resolved, damages are smaller. Further, most damage studies are done in the developed world, and the developing world is less able to adapt to climate change. Hence damage studies need to be expanded, and the results need to be incorporated into IAMs.

While sensitivity analysis gives important insights into the behavior of IAMs under alternative parameter specifications, sensitivity analysis falls well short of modeling optimal behavior under uncertainty. Direct incorporation of uncertainty goes a long way toward making the results more useful for policy-makers.

5. Conclusions

In the climate change literature, integrated assessment models have a relatively short history of less than a decade, yet a surprising amount of knowledge has emerged. Before the first IAM introduced by Nordhaus (1991), there was no clear way to combine the immense amounts of information on climate change. Hence, researchers and policy makers had little information about the expected costs, damages, and effects of climate change were. IAMs have now sucessfully integrated scientific information on climate change, and ordered together the various components of climate change. IAMs then pointed out the expected costs and benefits of climate change control, and the results surprised many climate change researchers and policy makers.

Probably the most striking result is that our current understanding of climate change costs, damages, etc. does not justify more than modest emissions control given a discount rate calibrated from interest rates and slow economic growth. The optimal amount of emissions control is well below current proposed policies, yet more than the current policy of doing nothing. The result holds up surprisingly well to sensitivity analysis with respect to many uncertainties. However, IAMs do show the sensitivity of emissions policy to the treatment of future generations through the discount rate and to estimates of economic growth. Other results include that information acquisition makes little difference to current period levels of emissions control, and the cost of following other proposed emissions policies.

Many challenges still remain, but the above conclusions are unlikely to be altered. A better, endogenous model of technical change is essential. Further, most models allow for an overly limited set of responses on the part of consumers and producers in the model, especially in modeling adjustment costs and damages. Most models still rely on certainty equivalence, which does not hold, in uncertainty analysis. However, preliminary work indicates the above results on modest controls and sensitivity to the discount rate are not altered when endogenous technical change or actual decision making under uncertainty are considered. Finally, recent work on calibrating the damage from climate change needs to be expanded and incorporated into IAMs, which now use expert surveys or best guesses.

The integrated assessment community has done an excellent job of analyzing, comparing, and contrasting the multitude of IAMs. Because of the analysis, IAMs give a remarkably consistent message. However, despite the consistent message and the large amount of government research money which has been spent, the message is not known far outside the integrated assessment community. The integrated assessment community must still do more to bring the results to the forefront of the debate on what to do about climate change.

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Reference

J. Alcamo (ed.), *Image 2.0: Integrated Modeling of Global Climate Change* (Kluwer, Dordrecht, The Netherlands, 1994).

K. Arrow, et. al., “Intertemporal Equity, Discounting, and Economic Efficiency,” pp. 130-144 in J. P. Bruce, et. al. (eds), *Climate Change 1995: Economic and Social Dimensions of Climate Change*, Cambridge University Press, Cambridge (1996).

R. Balvers and T. Cosimano, “Actively Learning About Demand and the Dynamics of Price Adjustment,” *The Economic Journal*, 100:882-98 (1990).

G. W. Bassett, Jr., "Breaking Recent Global Temperature Records," *Climatic Change*, 21:303-315 (1992).

T. Chapuis, M. Dong, and M. Grubb, “The Greenhouse Cost Model: An Exploration of the Implications for Climate Change Policy of Inertia and Adaptability in Energy Systems,” International Energy Workshop, IIASA, Laxenburg, Austria, June 20-22 (1995).

W. Cline, *The Economics of Global Warming* (Institute for International Economics, Washington, DC, 1992).

D. Cohan, R. Stafford, J. Scheraga, and S. Herrod, "The Global Climate Policy Evaluation Framework," *Proc., 1994 A&WMA Global Climate Change Conference*, Apr. 5-8, 1994, Phoenix.

Commission of the European Communities (CEC), *PAGE User Manual* (Brussels, 1992).

M.A. Cunha-e-sa, "Essays in Environmental Economics," Ph.D. dissertation, Dept. of Economics, University of Illinois, Urbana, Illinois (1994).

H. Dowlatabadi and M. G. Morgan, "A Model Framework for Integrated Assessment of the Climate Problem," mimeo, Department of Engineering and Public Policy, Carnegie Mellon University 1995.

H. Dowlatabadi, "Integrated Assessment Climate Assessment Model 2.0, Technical Documentation," *Energy Policy*, 21:209-221 (1993).

J. Edmonds, J. Pitcher, N. Rosenberg, and T. Wigley, "Design for the Global Change Assessment Model," *Proc., International Workshop on Integrative Assessment of Mitigation, Impacts and Adaptation to Climate Change*, Oct. 13-15, 1994, IIASA, Austria.

Energy Modeling Forum, "Reducing Global Carbon Emissions-Costs and Policy Options," mimeo, EMF-12, Stanford University, 1993.

B. S. Fisher, et. al., "An Economic Assessment of Policy Instruments for Combating Climate Change," pp. 401-433 in J. P. Bruce, et. al. (eds), *Climate Change 1995: Economic and Social Dimensions of Climate Change*, Cambridge University Press, Cambridge (1996).

C. Folland, T. Karl, and K. Vinnikov, "Observed Climate Variation and Change," pp. 194-238 in J. T. Houghton, et. al. (eds), *Climate Change*, *The IPCC Scientific Assessment*, Cambridge University Press, Cambridge (1990).

L. H. Goulder, "Effects of Carbon Taxes in an Economy with Prior Tax Distortions: An Intertemporal General Equilibrium Analysis," *Journal of Environmental Economics and Management*, 29(3):271-297 (1995).

L. H. Goulder and S. H. Schneider, “Induced Technological Change, Crowding Out, and the Attractiveness of CO_2 Emissions Abatement,” mimeo, Stanford University, 1996.

J.K. Hammitt, “Expected Values of Information and Cooperation for Abating Global Climate Change,” in R. Keeney, et. al. (eds), *Wise Choices: Games Decisions and Negotiations*, Harvard Business School Press, Cambridge (1995).

J.K. Hammitt, R.J. Lempert and M.E. Schlesinger, "A Sequential-Decision Strategy for Abating Climate Change," *Nature*, 357:315-318 (1992).

David L. Kelly and Charles D. Kolstad, “Malthus and Climate: Betting on a Stable Population,” mimeo, UCSB Economics Department, February 1996.

David L. Kelly and Charles D. Kolstad, “Bayesian Learning, Growth, and Pollution,” forthcoming, *J. Econ. Dynamics and Control*.

David L. Kelly, Charles D. Kolstad, Michael E. Schlesinger, and Natalia G. Andronova, “Learning About Climate Sensitivity from the Instrumental Temperature Record” mimeo, UCSB Economics Department, January, 1998.

Charles D. Kolstad, "Looking vs. Leaping: The Timing of CO_2 Control in the Face of Uncertainty and Learning," pp. 63-82 in Y. Kaya, N. Nakicenovic, W. D. Nordhaus and F. L. Toth (eds), *Costs, Impacts and Benefits of CO_2 Mitigation*, IIASA, Austria (June 1993).

Charles D. Kolstad, "Learning and Stock Effects in Environmental Regulation: The Case of Greenhouse Gas Emissions," *Journal of Environmental Economics and Management*, 31:1-18 (1996).

D. Laibson, "Hyperbolic Discount Functions, Undersaving, and Savings Policy," mimeo, Harvard University, 1996.

R. Lind, "Intergenerational Equity, Discounting, and the Role of Cost-Benefit Analysis in Evaluating Global Climate Policy," pp. 447-466 in N. Nakicenovic, et. al. (eds), *Integrative Assessment of Mitigation, Impacts, and Adaptation to Climate Change*, IIASA, Austria (October 1994).

R.J. Lempert, M.E. Schlesinger and S.C. Banks, "When We Don't Know the Costs or Benefits: Adaptive Strategies for Abating Climate Change," *Climatic Change*, 33:235-74 (1996).

R.J. Lempert, M.E. Schlesinger and J.K. Hammitt, "The Impact of Potential Abrupt Climate Changes on Near-Term Policy Choices," *Climatic Change*, 26:351-76 (1994).

D. Maddison, "A Cost-Benefit Analysis of Slowing Climate Change," *Energy Policy*, 23(4/5):337-346 (1995).

A.S. Manne, "Intergenerational Altruism, Discounting and the Greenhouse Debate," mimeo, Stanford University, 1996.

A.S. Manne and R.G. Richels, *Buying Greenhouse Insurance: The Economic Costs of CO_2 Emission Limits*, (MIT Press, Cambridge, Mass., 1992).

A.S. Manne, R. Mendelsohn, and R.G. Richels, "MERGE: A Model for Evaluating Regional and Global Effects of GHG Reduction Policies" *Energy Policy*, 23(1):17-34 (1993).

A.S. Manne and R.G. Richels, "CO_2 Hedging Strategies-The Impact of Uncertainty on Emissions," paper presented at the OECD/IEA Conference on the Economics of Climate Change, Paris 14-16 June, 1993.

A.S. Manne and R.G. Richels, “On Stabilizing CO_2 Concentrations- Cost-Effective Emissions Reductions Strategies,” mimeo, Stanford University, 1997.

Massachusetts Institute of Technology (MIT), *Joint Program on the Science and Technology of Global Climate Change* (Cambridge, 1994).

D. Meadows, et. al., *The Limits to Growth* (Universe Books, New York, 1972).

R. Mendelsohn, et. al., "The Market Impacts of Climate Change in the US," mimeo, Yale University, 1996.

R. Mendelsohn, W. Nordhaus, and D. Shaw, "The Impact of Global Warming on Agriculture, a Ricardian Analysis," *American Economic Review*, 84(4):753-770 (1994).

S. Mori, “Long-Term Interactions Among Economy, Environment, Energy, and Land-use Changes – An Extension of MARIA Model,” Technical Report IA-TR-95-04, Science University of Tokyo, Japan.

T. Morita, et. al., “AIM-Asian-Pacific Integrated Model for Evaluating Policy Options to Reduce GHG Emissions and Global Warming Impacts, Interim Report,” mimeo National Institute for Environmental Studies, Tsukuba, Japan, 1994.

W. D. Nordhaus, *Managing the Global Commons: The Economics of Climate Change* (MIT Press, Cambridge, Mass., 1994).

W. D. Nordhaus and G. Yohe, “Future Paths of Energy and Carbon Dioxide Emissions” in *Climate Change*, National Academy Press (1983).

W. D. Nordhaus, "To Slow or not to Slow: The Economics of the Greenhouse Effect," *The Economic Journal*, 101:920-37 (1991).

W. D. Nordhaus and Z. Yang, "A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies," *American Economic Review*, 86:741-65 (1996).

S. C. Peck, H-P Chao, and T.J. Teisberg, "Optimal Control and Learning Strategies when Environmental Costs are Cumulative," *Proc., IFAC/IFORS/IAEE International Symposium on Energy Systems, Management and Economics*, Oct. 25-7, 1989, Tokyo.

S.C. Peck and T.J. Teisberg, "CETA: A Model for Carbon Emissions Trajectory Assessment," *Energy Journal*, 13(1):55-77 (1992).

R. Richels and J. Edmonds, "The Cost of Stabilizing Atmospheric CO_2 Emissions," *Energy Policy*, 23(4/5):373-378 (1995).

J. Rotmans, *TARGETS in Transition*, RIVM report, Rijksinstitut Voor Volksgezondheid En Milieuhygiene (National Institute of Public Health and the Environment), Bilthoven, The Netherlands, 1995.

T. Schelling, "Intergenerational Discounting," *Energy Policy*, 23:395-401 (1995).

Michael E. Schlesinger and Navin Ramankutty, "Is the recently reported 65- to 70-year surface-temperature oscillation the result of climatic noise?," *J. Geophysical Research*, 100 (07):13767-74 (1995).

R. Tol, et. al., *The Climate Fund: Some Notions on the Socio-Economic Impacts of Greenhouse Gas Emissions and Emission Reduction in an International Context* (V.U. Boekhandel/Uitgeverij, Netherlands, 1995).

United Nations, *World Population Prospects: The 1994 Revision* (United Nations, New York, 1994).

R. Watson, et. al., "Greenhouse Gasses and Aerosols," pp. 1-40 in J. T. Houghton, et. al. (eds), *Climate Change, The IPCC Scientific Assessment*, Cambridge University Press, Cambridge (1990).

M. Weitzman, "On the 'Environmental' Discount Rate," *Journal of Environmental Economics and Management*, 26:200-209 (1994).

M. Weitzman, "Why the Far-Distant Future Should be Discounted at its Lowest Possible Rate," mimeo, Harvard University, 1997.

Weyant, et. al., "Integrated Assessment of Climate Change: An Overview and Comparison of Approaches and Results," pp. 367-439 in J. P. Bruce, et. al. (eds), *Climate Change 1995: Economic and Social Dimensions of Climate Change*, Cambridge University Press, Cambridge (1996).

T. Wigley and T. Barnett, "Detection of the Greenhouse Effect in the Observations," pp. 239-255 in J. T. Houghton, et. al. (eds), *Climate Change, The IPCC Scientific Assessment*, Cambridge University Press, Cambridge (1990).

World Bank, *World Development Report* (Oxford University Press, 1991).

G. Yohe and R. Wallace, "Near Term Mitigation Policy for Global Change Under Uncertainty: Minimizing the Expected Cost of Meeting Unknown Concentration Thresholds," mimeo, Wesleyan University, 1995.

Table I: A survey of IAMs.

Model	Author	Type	Detail			Uncertainty	Economic Response
			C	E	A		
AIM	Morita et al (1994)	Evaluation	C	S	C	None	None
AS/ExM	Lempert, et. al. (1996)	Evaluation	C	S	C	Discrete	None
CETA	Peck and Tiesberg (1992)	Optimization	S	C	S	Discrete	Investment, energy
Connecticut	Yohe and Wallace (1995)	Optimization	S	C	S	Discrete	Investment, energy
CRAPS	Hammit (1995)	Optimization	S	S	S	Discrete	None
CSERGE	Maddison (1995)	Optimization	S	S	S	Stochastic sim.	None
DIAM	Chapuis, et. al. (1995)	Optimization	S	S	S	None	None
DICE	Nordhaus (1994)	Optimization	S	S	S	Stochastic sim.	Investment
FUND	Tol et al (1995)	Optimization	S	S	S	Stochastic sim.	None
ICAM	Dowlatabadi and Morgan (1995)	Evaluation	C	S	C	Stochastic sim.	None
IMAGE	Alcamo (1994)	Evaluation	C	S	C	Sensitivity	None
MAGICC	Wigley, et. al. (1993)	Evaluation	C	C	C	Sensitivity	None
MARIA	Mori (1995)	Optimization	S	C	S	None	Investment, energy
MERGE	Manne, et. al. (1993)	Optimization	S	C	S	Discrete	Investment, energy
MIT	MIT (1994)	Evaluation	C	C	C	Stochastic sim.	None
PAGE	CEC (1992)	Evaluation	C	C	S	Stochastic sim.	None
PEF	Cohan, et. al. (1994)	Evaluation	C	S	S	Stochastic sim.	None
ProCAM	Edmonds, et. al. (1994)	Evaluation	C	C	C	Sensitivity	None
RICE	Nordhaus and Yang (1996)	Optimization	S	C	S	None	Investment, control*
SLICE	Kolstad (1996), Kelly and Kolstad (forthcoming)	Optimization	S	S	S	Continuous	Investment
TARGETS	Rotmans (1995)	Evaluation	C	S	C	None	None

Key:

Detail: Three categories are climate (C), economy (E), and atmospheric chemistry (A). Detail refers to either simple (S) or complex (C).

Type: Evaluation means a model that evaluates an exogenous policy; optimization endogenously find the optimal policy.

Uncertainty: Sensitivity analysis indicates certainty equivalence is assumed. Stochastic simulation also assumes certainty equivalence but varies parameters together. Discrete indicates decision making under uncertainty, where possible outcomes are discrete (usually only two possible outcomes), and learning is passive. Continuous indicates a continuous distribution of outcomes of uncertainty at all time periods and active learning.

Economic Response: Investment indicates agents can change investment/consumption decisions in response to GHG control policies. Energy indicates agents can change energy sources or the capital energy ratio in response to GHG control policy. RICE model allows for economic response of agents investment and control decisions to investment and control decisions made in other regions.