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Lessons for mitigation from the foundations of monetary policy in the United States

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24.1 Introduction

Many analysts, (including Pizer [Chapter 25], Keller *et al.* [Chapter 28], Webster [Chapter 29] and Toth [Chapter 30] in this volume, as well as others like Nordhaus and Popp [1997], Tol [1998], Lempert and Schlesinger [2000], Keller *et al.* [2004] and Yohe *et al.* [2004]) have begun to frame the debate on climate change mitigation policy in terms of reducing the risk of intolerable impacts. In their own ways, all of these researchers have begun the search for robust strategies that are designed to take advantage of new understanding of the climate systems as it evolves – an approach that is easily motivated by concerns about the possibility of abrupt climate change summarized by, among others, Alley *et al.* (2002). These concerns take on increased importance when read in the light of recent surveys which suggest that the magnitude of climate impacts (see, for example, Smith and Hitz [2003]) and/or the likelihood of abrupt change (IPCC, 2001; Schneider, 2003; Schlesinger *et al.*, 2005) could increase dramatically if global mean temperatures rose more than 2 or 3 °C above pre-industrial levels. Neither of these suggestions can be advanced with high confidence, of course, but that is the point. Uncertainty about the future in a risk-management context becomes *the fundamental reason* to contemplate action in the near term even if such action cannot guarantee a positive benefit–cost outcome either in all states of nature or in expected value.

Notwithstanding the efforts of these and other scholars to reflect these sources of concern in their explorations of near-term policy intervention, the call for a risk-management approach has fallen on remarkably deaf ears. Indeed, uncertainty is frequently used by many in the United States policy community and others in the consulting business as *the fundamental reason* not to act in the near term. For evidence of this tack, consider the policy stance of the Bush Administration that was introduced in 2002. In announcing his take on the climate issue, the President emphasized that "the policy challenge is to act in a serious and sensible way, *given our knowledge*. *While scientific uncertainties remain*, we can begin now to address the factors that contribute to climate change" (www.whitehouse.gov/ new/releases/2002/02/climate change.html; my emphasis). Indeed, the *New York Times* reported on June 8th, 2005 that Philip Cooney, the White House Council on Environmental Quality, repeatedly inserted references to "significant and fundamental" uncertainties into official documents that describe the state of climate science even though he has no formal scientific training (Revkin, 2005). In large measure responding to concerns about uncertainty among his closest advisers, the President's policy called for more study, for voluntary restraint (by those motivated to reduce their own emissions even though others are not), and for the development of alternatives to current energy-use technologies (because reducing energy dependence is otherwise a good idea even though promising advancements face enormous difficulty penetrating the marketplace).

If productive dialogue is to resume, advocates of risk-based near-term climate policy will have to express its value in terms that policymakers will understand and accept. The case must be made, in other words, *that a risk-management approach to near-term climate policy would be nothing more than the application of already accepted policy-analysis tools and principles to a new arena*. This paper tries to contribute to this process by turning for support to recent descriptions of how

Human-induced Climate Change: An Interdisciplinary Assessment, ed. Michael Schlesinger, Haroon Kheshgi, Joel Smith, Francisco de la Chesnaye, John M. Reilly, Tom Wilson and Charles Kolstad. Published by Cambridge University Press. © Cambridge University Press 2007.

monetary policy is conducted in the United States. Opening remarks offered by Alan Greenspan, Chairman of the Federal Reserve Board, at a symposium that was sponsored by the Federal Reserve Bank of Kansas City in August 2003 are a great place to start (Greenspan, 2003). In his attempt to motivate three days of intense conversation among policy experts, Chairman Greenspan observed:

> For example, policy A might be judged as best advancing the policymakers' objectives, conditional on a particular model of the economy, but might also be seen as having relatively severe adverse consequences if the true structure of the economy turns out to be other than the one assumed. On the other hand, policy B might be somewhat less effective under the assumed baseline model ... but might be relatively benign in the event that the structure of the economy turns out to differ from the baseline. *These considerations have inclined the Federal Reserve policymakers toward policies that* ***limit the risk*** *of deflation even though the baseline forecasts from most conventional models would* ***not project such an event.*** (Greenspan (2003), p. 4; my emphasis).

The Chairman expanded on this illustration in his presentation to the American Economic Association (AEA) at their 2004 annual meeting in San Diego:

> ... the conduct of monetary policy in the United States has come to involve, at its core, crucial elements of risk management. This conceptual framework emphasizes understanding as much as possible the many sources of risk and uncertainty that policymakers face, quantifying those risks *when possible*, and assessing the costs associated with each of the risks....... This framework also entails, in light of those risks, a strategy for policy directed at maximizing the probabilities of achieving over time our goals ... Greenspan (2004), p. 37; my emphasis).

Clearly, these views are consistent with an approach that would expend some resources over the near term to avoid a significant risk (despite a low probability) in the future. Indeed, the Chairman used some familiar language when he summarized his position:

> As this episode illustrates (the deflation hedge recorded above), policy practitioners under a risk-management paradigm may, at times, be led to undertake actions intended to provide *insurance against especially adverse outcomes*. (Greenspan (2004), p. 37; my emphasis).

So how did the practitioners of monetary policy come to this position? By some trial and error described by Greenspan in his AEA presentation, to be sure; but the participants at the earlier Federal Reserve Bank symposium offer a more intriguing source. Almost to a person, they all argued that the risk-management approach to monetary policy evolved most fundamentally from a seminal paper authored by William Brainard (1967); see, for example, Greenspan (2003), Reinhart (2003), and Walsh (2003).

This paper is crafted to build on their attribution by working climate into Brainard's modeling structure in the hope that it might thereby provide the proponents of a risk-based approach to climate policy some access to practitioners of macroeconomic policy who are familiar with its structure and its evolution since 1967. It does so even though the agencies charged with crafting climate policy in the United States (the Department of State, the Department of Energy, the Environmental Protection Agency, the Council for Environmental Quality, etc.) are not part of the structure that crafts macroeconomic policy (the Federal Reserve Board, the Treasury, the Council of Economic Advisors, etc.). The hope, therefore, is really that the analogy to monetary policy will spawn productive dialogue between the various offices where different policies are designed and implemented, even as it provides the environmental community with an example of a context within which risk-management techniques have informed macroscale policies.

The paper begins with a brief review of the Brainard (1967) structure with and without a climate policy lever and proceeds to explore the circumstances under which its underlying structure might lead one to appropriately ignore its potential. Such circumstances can and will be identified in Sections 24.2 and 24.3, but careful inclusion of a climate policy lever makes it clear that they are rare even in the simple Brainard-esque policy portfolio. In addition, manipulation of the model confirms that the mean effectiveness of any policy intervention, the variance of that effectiveness and its correlation with stochastic influences on outcome are all critical characteristics of any policy. Section 24.4 uses this insight as motivation when the text turns to describing some results drawn from the Nordhaus and Boyer (2001) DICE model that has been expanded to accommodate profound uncertainty about the climate's temperature sensitivity to increases in greenhouse gas concentrations. Concluding remarks use these results, cast in terms of comparisons of several near-term policy alternatives, to make the case that creative and responsive climate policy can be advocated on the basis of the same criteria that led the Federal Reserve System of the United States to adopt a risk-management approach to monetary policy.

24.2 The Brainard model

The basic model developed by Brainard (1967) considers a utility function on some output variable y (read GDP, for example) of the form:

$$V(y) = -(y - y^*)^2, \tag{24.1a}$$

where y^* represents the targeted optimal value. The function $V(y)$ fundamentally reflects welfare losses that would accrue if actual outcomes deviate from the optimum. The correlation between y and some policy variable P (read a monetary policy indicator such as the discount rate, for example) is taken to be linear, so

$$y = aP + \varepsilon.$$

In specifying this relationship, a is a parameter that determines the ability of policy P to alter output and ε is an unobservable random variable with mean μ_ε and variance σ_ε^2. The expected value of utility is therefore

$$\begin{aligned} E\{V(y)\} &= -E\{y^2 - 2yy^* + (y^*)^2\} \\ &= -\{E(y^2) - 2y^*E(y) + (y^*)^2\} \\ &= -\{\mu_y{}^2 - \sigma_y{}^2 - 2y^*\mu_y + (y^*)^2\} \\ &= -\{\sigma_y{}^2 + (\mu_y - y^*)^2\}. \end{aligned} \quad (24.1b)$$

In this formulation, of course, σ_y^2 and μ_y represent the variance and mean of y, respectively, given a policy intervention through P and the range of possible realizations of a and ε.

If the decisionmaker knew the value of parameter $a = a_o$ with certainty, then $\sigma_y^2 = \sigma_\varepsilon^2$. Moreover, prescribing a policy P_c such that $\mu_y = y^*$ would maximize expected utility. In other words,

$$P_c = \{y^* - \mu_\varepsilon\}/a_o \quad (24.2a)$$

In an uncertain world where a is known only up to its mean μ_a and variance σ_a^2, however,

$$\mu_y = \mu_a P + \mu_\varepsilon \text{ and}$$

$$\sigma_y^2 = P^2\sigma_a^2 + \sigma_\varepsilon^2$$

under the assumption that a and ε are independently distributed. Brainard focused his attention primarily on estimation uncertainty, but subsequent applications of his model (see, for example, Walsh [2003]) have also recognized many of the other sources that plague our understanding of the climate system – model, structural, and contextual uncertainties, to name just three.

The first-order condition that characterizes the policy P_u that would maximize expected utility in this case can be expressed as

$$\begin{aligned} \partial E\{V(y)\}/\partial P &= -\{2P_u\sigma_a^2 + 2(\mu_y - y^*)\mu_a\} \\ &= -\{2P_u\sigma_a^2 + 2(\mu_a P + \mu - y^*)\mu_a\} = 0 \end{aligned}$$

Collecting terms,

$$\begin{aligned} P_u &= \{(y^* - \mu_\varepsilon)\mu_a\}/\{\sigma_a{}^2 + \mu_a^2\} \\ &= P_c/\{(\sigma_a^2/\mu_a^2) + 1\} \end{aligned} \quad (24.2b)$$

under the assumption that the distribution of a is anchored with $\mu_a = a_o$. Notice that $P_u = P_c$ if uncertainty disappears as σ_a^2 converges to zero. If σ_a^2 grows to infinity, however, policy intervention becomes pointless and P_c collapses to zero. In the intermediate cases, Brainard's conclusion of caution – the "principle of attenuation" to use the phrase coined by Reinhart (2003) – applies. More specifically, policy intervention should be restrained under uncertainty about its effectiveness, at least in comparison with what it would have been if its impact were understood completely.

Reinhart (2003) and others have noted that considerable effort has been devoted to exploring the robustness of the Brainard insight in a more dynamic context where the loss function associated with deviations from y^* is not necessarily symmetric. They note, for example, that the existence of thresholds for $y < y^*$ below which losses become more severe at an increasing rate can lead to an intertemporal hedging strategy that pushes policy further in the positive direction in good times even at the risk of overshooting the targeted y^* with some regularity. Using such a strategy moves μ_ε higher over time so that the likelihood of crossing the troublesome threshold falls in subsequent periods. In the realm of monetary policy, for example, concerns about deflation have defined the critical threshold; in the realm of climate, the possibility of something sudden and non-linear such as the collapse of the Atlantic thermohaline circulation comes to mind as a critical threshold to be avoided by mitigation.

Practitioners of monetary policy have also worried about avoiding states of nature where the effectiveness of P can be eroded, and so they have found a second reason to support the sort of dynamic hedging just described. In these contexts, for example, central bankers have expressed concern that the ability of reductions in the interest rate to stimulate the real economy can be severely weakened if rates have already fallen too far. In the climate arena, decisionmakers may worry that it may become impossible to achieve certain mitigation targets over the long run if near-term interventions are too weak. This point is illustrated in Yohe *et al*. (2004) when certain temperature targets become infeasible if nothing is done over the next 30 years to reduce greenhouse gas emissions.

Both of these concerns lie at the heart of the Greenspan comparison of two policies, of course. However, neither confronts directly the question at hand: *under what circumstances (if any) can the effects of climate change on the real economy be handled by standard economic interventions without resorting to direct mitigation of the drivers of that change?*

24.3 Extending the model to include a climate module

To address this question, we add a climate module to the Brainard model so that we can search for conditions under which it would make sense for policymakers who have their hands on the macro-policy levers (the P in the basic model) to ignore climate policy when they formulate their plans. To that end, we retain the symmetric utility function recorded in Eq. (24.1a), but we add a new policy variable C (read mitigation for the moment) to the output relationship so that

$$y = aP + cC + \varepsilon.$$

The error term ε now includes some reflection of climate risk to the output variable. Since the expected value of utility is preserved, perfect certainty about a and now c still guarantees that $\sigma_y^2 = \sigma_\varepsilon^2$ so that prescribing a policy P_c such that $\mu_y = y^*$ would still maximize expected utility depicted by Eq. (24.1b).

In other words,

$$P_{\mathrm{c}} = \{y^* - \mu_\varepsilon\}/a_{\mathrm{o}}$$

would persist and the optimal intervention could be achieved without exercising the climate policy variable. In this certainty case, clearly, climate policy could be set equal to zero without causing any harm.

In an uncertain world where a and c are known only up to means (μ_a and μ_c) and variances (σ_a^2 and $\sigma_c{}^2$), however, we now have

$$\mu_y = \mu_a P + \mu_c C + \mu_\varepsilon \text{ and } \sigma_y{}^2 = P^2\sigma_a^2 + C^2\sigma_c{}^2 + \sigma_\varepsilon^2$$

under the assumption that a, c and ε are all independently distributed. We already know that this sort of uncertainty can modify the optimal policy intervention, but does it also influence the conclusion that the climate policy lever could be ignored?

24.3.1 The climate lever in an isolated policy environment

To explore this question, note that Eq. (24.2b) would still apply for setting policy P if the policymaker chose to ignore the climate policy variable; i.e.,

$$P_{\mathrm{uo}} = P_{\mathrm{u}} \ = \ P_{\mathrm{c}}/\{(\sigma_a^2/\mu_a^2) + 1\}.$$

As a result, the first-order condition characterizing the policy C_{uo} that would maximize expected utility can be expressed as

$$\partial E\{V(y)\}/\partial C = -\{2C_{\mathrm{uo}}\sigma_c{}^2 + 2(\mu_\varepsilon - y^* + \mu_a P_u + \mu_c C_{\mathrm{uo}})\mu_c\} = 0$$

Collecting terms,

$$C_{\mathrm{uo}} = \{[\sigma_a^2\mu_c^2]/[D_a D_c]\}\{(y^* - \mu_\varepsilon)/\mu_c\}, \qquad (24.3)$$

where

$$D_a \equiv \{\sigma_a^2 + \mu_a^2\} \text{ and } D_c \equiv \{\sigma_c^2 + \mu_c^2\}.$$

Notice that $C_{\mathrm{uo}} = 0$ if uncertainty about the effectiveness of P disappeared as σ_a^2 converged to zero. The climate policy lever could therefore still be ignored even in the context of uncertainty drawn from our understanding of the climate system, in this case. This would not mean, however, that climate change should be ignored. The specification of P_{uo} would recognize the effect of climate through its effect on μ_ε.

If σ_a^2 grew to infinity, however, then l'Hospital's rule shows that policy intervention through C would dominate. Indeed, in this opposing extreme case,

$$C_{\mathrm{uo}} = \{(y^* - \mu_\varepsilon)/\mu_c\}/\{(\sigma_c^2/\mu_c^2) + 1\} \qquad (24.4)$$

so that policy intervention through C would mimic the original intervention through P while P_{uo} collapsed to zero. In the more likely intermediate cases in which the variances of both policies are non-zero but finite, the optimal setting for climate policy would be positive as long as $\mu_c > 0$.

It follows, from consideration of the intermediate cases, that bounded uncertainty about the effectiveness of both policies can play a critical role in determining the relative strengths of climate and macroeconomic policies in the policy mix. *Put another way, uncertainty about the effectiveness of either or both policies becomes the reason to diversify the intervention portfolio by undertaking some climate policy even if the approach taken in formulating other policies remains unchanged. Moreover, the smaller the uncertainty about the link between climate policy C and output, the larger should be the reliance on climate mitigation.*

24.3.2 The climate lever in an integrated policy environment

These observations fall short of answering the question of how best to integrate macroeconomic and climate policy in an optimal intervention portfolio. Maximizing expected utility if both policies were considered together in a portfolio approach would produce two first-order conditions:

$$\partial E\{V(y)\}/\partial P = -\{2P_{\mathrm{u}}T\sigma_a^2 + 2(\mu_\varepsilon - y^* + \mu_a P_{uT} + \mu_c C_{\mathrm{uT}})\mu_a\} = 0 \text{ and}$$

$$\partial E\{V(y)\}/\partial C = -\{2C_{\mathrm{u}}T\sigma_c^2 + 2(\mu_\varepsilon - y^* + \mu_a P_{\mathrm{uT}} + \mu_c C_{\mathrm{uT}})\mu_c\} = 0.$$

In recording these conditions, P_{uT} and C_{uT} represent the jointly determined optimal choices for P and C, respectively. Solving simultaneously and collecting terms,

$$P_{\mathrm{uT}} = \{[\sigma_c^2\mu_a^2]/[D_a D_c - \mu_a^2\mu_c^2]\}\{(y^* - \mu_\varepsilon)/\mu_a\}, \text{ and} \qquad (24.5a)$$

$$C_{\mathrm{uT}} = \{[\sigma_a^2\mu_c^2]/[D_a D_c - \mu_a^2\mu_c^2]\}\{(y^* - \mu_\varepsilon)/\mu_c\}. \qquad (24.5b)$$

Table 24.1 shows the sensitivities of these policies to extremes in the characterizations of the distributions of the parameters a and c. Notice that the policy specifications recorded in Eq. (24.5a and b) collapse to the certainty cases for C and P if the variance of c or a (but not both) collapses to zero, respectively. The policies also converge to the characterizations in Eq. (24.2b) or (24.4) if the variances of a or c grow without bound, respectively (again by virtue of l'Hospital's rule). In between these extremes, Eq. (24.5a and b) show how ordinary economic and climate policies can be integrated to maximize expected utility. In this regard, it is perhaps more instructive to contemplate their ratio:

$$\{C_{\mathrm{uT}}/P_{\mathrm{uT}}\} = \{[\sigma_a^2\mu_c]/[\sigma_c^2\mu_a]\}. \qquad (24.6)$$

Equation (24.6) makes it clear that climate policy should be exercised relatively more vigorously if the variance of its effectiveness parameter falls or if its mean effectiveness

Table 24.1 Integrating policies in the extremes.

Limiting case	$C_{\mathbf{uT}}$	$P_{\mathbf{uT}}$
$\sigma_c{}^2 \to \infty$ with $0 < \sigma_a{}^2 < \infty$ (i.e., $D_c \to \infty$)	$C_{\mathrm{uT}} \to 0$	$P_{\mathrm{uT}} \to \{(y^* - \mu)/\mu_a\}/\{(\sigma_a{}^2 / \mu_a{}^2) + 1\}$
$\sigma_c{}^2 \to 0$ with $0 < \sigma_a{}^2 < 8\infty$ (i.e., $D_c \to \mu_c{}^2$)	$C_{\mathrm{uT}} \to \{(y^* - \mu_\varepsilon)/\mu_c\}$	$P_{\mathrm{uT}} \to 0$
$\sigma_a{}^2 \to \infty$ with $0 < \sigma_c^2 < \infty$ (i.e., $D_a \to \infty$)	$C_{\mathrm{uT}} \to \{(y^* - \mu_\varepsilon)/\mu_c\}/ \{(\sigma_c^2/\mu_c^2)+1\}$	$P_{\mathrm{uT}} \to 0$
$\sigma_a{}^2 \to \infty$ with $0 < \sigma_c^2 < \infty$ (i.e., $D_a \to \mu_a{}^2$)	$C_{\mathrm{uT}} \to 0$	$P_{\mathrm{uT}} \to \{(y^* - \mu_\varepsilon)/\mu_a\}$
$\sigma_c{}^2 = 0$ and $\sigma_a{}^2 = 0$	Undefined	Undefined

increases. In addition, comparing Eq. (24.2b) and (24.5a) shows that

$$\{P_{\mathrm{u}}/P_{\mathrm{uT}}\} = \{D_c/\sigma_c^2\} + \{\mu_a^2\mu_c^2/\sigma_c^2 D_a\} > 1;$$

i.e., an integrated approach diminishes the role of ordinary economic policy in a world that adds climate to the sources of uncertainty to which it must cope as long as σ_c^2 is bounded.

It is, of course, possible to envision responsive climate policy that corrects itself as our understanding of the climate system evolves – ramping up (or damping) the control if it became clear that damages were more (less) severe than expected and/or critical thresholds were closer (more distant) than anticipated. In terms of the Brainard model, this sort of properly designed responsive policy would create a negative covariance between the effectiveness parameter c and the random variable ε. Since the variance of output is given by

$$\sigma_y^2 = P^2\sigma_a^2 + C^2\sigma_c^2 + \mathrm{cov}(c;\varepsilon) + \sigma_\varepsilon^2,$$

in this case, repeating the optimization exercise reveals that

$$\begin{aligned} P'_{\mathrm{uT}} &= \{[\sigma_c^2\mu_a^2]/[D_a D_c - \mu_a^2\mu_c^2]\}\{(y^* - \mu_\varepsilon)/\mu_{\mathrm{a}}\} \\ &\quad + \{\mathrm{cov}(c;\varepsilon)/D_a\} \qquad (24.7\mathrm{a}) \\ &= P_{\mathrm{uT}} + \{\mathrm{cov}(c;\varepsilon)/D_a\} < P_{\mathrm{uT}} \end{aligned}$$

and

$$\begin{aligned} C'_{\mathrm{uT}} &= \{[\sigma_a^2\mu_c^2]/[D_a D_c - \mu_a^2\mu_c^2]\}\{(y^* - \mu_\varepsilon)/\mu_{\mathrm{c}}\} \\ &\quad - \{\mathrm{cov}(c;\varepsilon)/D_{\mathrm{c}}\} \qquad (24.7\mathrm{b}) \\ &= C_{\mathrm{uT}} - \{\mathrm{cov}(c;\varepsilon)/D_{\mathrm{c}}\} > C_{\mathrm{uT}} \end{aligned}$$

As should be expected, the ability of responsive climate policy to deal more effectively with worsening climate futures would increase its emphasis in an optimizing policy mix at the expense of ordinary economic policy intervention.

24.3.3 Discussion

Equation (24.6) shows explicitly that an integrated policy portfolio would ignore climate policies at its increasing peril, especially if the design of the next generation of climate policy alternatives could produce smaller levels of implementation uncertainty. Targeting something closer to where impacts are felt in the causal chain (like shooting for a temperature limit rather than trying to achieve emissions pathways whose associated impacts are known with less certainty) could, for example, be preferred in the optimization framework if the technical details of monitoring and reacting could be overcome. As in any economic choice, however, there are tradeoffs to consider. Moving to the impact end of the system should reduce uncertainty on the damages side of the implementation calculus (if monitoring, attribution, and response could all be accomplished in a timely fashion, of course), but it could also increase uncertainty on the cost side.

In any case, Eq. (24.7a and b) show that the potential advantage of climate policy could turn on the degree to which its design could accommodate a negative correlation. They support consideration of a comprehensive climate policy that could incorporate mechanisms at some level by which mitigation could be predictably adjusted as new scientific understanding of the climate system, climate impacts, and/or the likelihood of an abrupt or non-linear change became available (much in the same way that the rate of growth of the money supply can be predictably adjusted in response to changes in the overall health of the macroeconomy).

In addition, the same caveats discovered by the practitioners of monetary policy certainly apply to the climate side of the policy mix. Considering combined policies in a dynamic context, that includes critical thresholds beyond which abrupt, essentially unknown but potentially damaging impacts could occur, would still support more vigorous intervention; and climate policy should be particularly favored for this intervention if it becomes more effective in avoiding those thresholds when crossing their boundaries becomes more likely. Indeed, the Greenspan warning can be especially telling in these cases.

24.4 The hedging alternative under profound uncertainty about climate sensitivity

The Brainard structure is highly abstract, to be sure, and so conclusions drawn from its manipulation beg the question of its applicability to the climate policy question as currently formulated. This section confronts this question directly by exercising a version of the Nordhaus and Boyer (2001) DICE integrated assessment model that has been modified to accommodate wide uncertainty in climate sensitivity *and* the

Table 24.2 Calibrating the climate module.

Climate sensitivity	Likelihood	Alpha-1 calibration
1.5 degrees	0.30	0.065742
2 degrees	0.20	0.027132
3 degrees	0.15	0.014614
4 degrees	0.10	0.011550
5 degrees	0.07	0.010278
6 degrees	0.05	0.009589
7 degrees	0.03	0.009157
8 degrees	0.03	0.008863
9 degrees	0.07	0.008651

Source: Yohe *et al*. (2004).

problem of setting near-term policy with the possibility of making "midcourse" adjustments sometime in the future.[1] It begins with a description of uncertainty in our current understanding of climate sensitivity. It continues to describe the modifications that were implemented in the standard DICE formulation, and it concludes by reviewing the relative efficacy, expressed in terms of expected net present value of gross world (economic) product (GWP), of several near-term policy alternatives.

24.4.1 A policy hedging exercise built around uncertainty about climate sensitivity

Andronova and Schlesinger (2001) produced a cumulative distribution of climate sensitivity based on the historical record. Table 24.2 records the specific values of a discrete version of this CDF that was used in Yohe *et al*. (2004) to explore the relative efficacy of various near-term mitigation strategies. There, the value of hedging in the near term was evaluated under the assumption that the long-term objective would constrain increases in global mean temperature to an unknown target. Calibrating the climate module of DICE to accommodate this range involved specifying both a climate sensitivity and an associated parameter that reflects the inverse thermal capacity of the atmospheric layer and the upper oceans in its reduced-form representation of the climate system. Larger climate sensitivities were correlated with smaller values for this capacity so that the model could match observed temperature data when run in the historical past. The capacity parameter was defined from optimization of the global temperature departures, calculated by DICE, and calibrated against the observed temperature departures from Jones and Moberg (2003) for the prescribed range of the climate sensitivities from 1.5 through 9 °C.

[1] Climate sensitivity is defined as the increase in equilibrium global mean temperature associated with a doubling of greenhouse gas concentrations above pre-industrial levels, expressed in terms of CO_2 equivalents.

It is widely understood that adopting a risk-management approach means that near-term climate policy decisions should, as a matter of course, recognize the possibility that adjustments will be possible as new information about the climate system emerges. The results that follow are the product of experiments that recognize this understanding. Indeed, they were produced by adopting the hedging environment that was created under the auspices of the Energy Modeling Forum in Snowmass to support initial investigations of the policy implications of extreme events; Manne (1995) and Yohe (1996) are examples of this earlier work. They were, more specifically, drawn from a policy environment in which decisionmakers evaluate the economic merits of implementing near-term global mitigation policies that would be in force for 30 years beginning in 2005 under the assumption that all uncertainty will be resolved in 2035. These global decision-makers would, therefore, make their choices with the understanding that they would be able to "adjust" their interventions in 2035 when they would be informed fully about both the climate sensitivity and the best policy target. In making both their initial policy choice and their subsequent adjustment, their goal was taken to be maximizing the expected discounted value of GWP across the range of options that would be available at that time.

The hedging exercise required several structural and calibration modifications of the DICE model in addition to changes in the climate module that were described above. Since responding to high sensitivities could be expected to put enormous pressure on the consumption of fossil fuel, for example, the rate of "decarbonization" in the economy (reduction in the ratio of carbon emissions to global economic output) was limited to 1.5% per year. Adjustments to mitigation policy were, in addition, most easily accommodated by setting initial carbon tax rates in 2005 and again in 2035. The initial and adjusted benchmarks appreciated annually at an endogenously determined return to private capital so that "investment" in mitigation was put on a par with investment in economic capital. Finally, the social discount factor for GWP included a zero pure rate of time preference in deference to a view that the welfare of future generations should not be diminished by the impatience of earlier generations for current consumption.

24.4.2 Some results

Suppose, to take a first example of how the critical mean, variance, and covariance variables from the Brainard foundations might be examined, that global decisionmakers tried to divine "optimal" intervention given the wide uncertainty about climate sensitivity portrayed in Table 24.2. Table 24.3 displays the means and standard deviations of the net value, expressed in terms of discounted value through 2200 and computed across the discrete range of climate sensitivities recorded in Table 24.2, for optimal policies that would be chosen if each of the climate sensitivities recorded in

Table 24.3 Exploring the economic value of deterministic interventions in the modified DICE environment. Mean returns in billions of 1995$ with the standard deviations in parentheses.

Policy context	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°
Economic value	68.34 (36.33)	86.36 (53.97)	95.38 (92.13)	84.21 (115.3)	72.38 (129.5)	62.59 (139.2)	54.05 (146.0)	44.65 (153.2)	44.65 (153.2)

Table 24.4 Exploring the economic value of the mean climate policy contingent on climate sensitivity in the modified DICE environment. Return in billions of 1995$ and maximum temperature change in °C.

Climate sensitivity	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°	Mean	Standard deviation
Economic value	0	52	125	164	186	200	209	215	219	96.62	81.94
Max ΔT	2.71	3.46	4.69	5.62	6.32	6.85	7.25	7.57	7.83	4.55	1.76

Table 24.5 Exploring the economic value of the responsive climate policy contingent on climate sensitivity in the modified DICE environment. Return in billions of 1995$ and maximum temperature change in °C.

Climate sensitivity	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°	Mean	Standard deviation
Economic value	25	58	126	177	212	236	256	271	281	117.82	90.11
Max ΔT	2.80	3.53	4.67	5.53	6.18	6.67	7.03	7.32	7.57	4.53	1.64

Table 24.2 were used to specify the uncontrolled baseline. The mean returns of these interventions peak for the policy associated with a 3 °C climate sensitivity, but the standard deviations grow monotonically with the assumed sensitivity. Selecting the mean of these interventions produces a net expected discounted value of $96.62 billion with a standard deviation of $81.94 billion. The first row of Table 24.4 shows the distribution of the underlying net values for this policy across the range of climate sensitivities, and the second row displays the associated maximum temperature increases that correspond to each policy.

Now suppose that decisionmakers recognized that a policy adjustment would be possible in 2035, but they could not tell in 2005 which one would be preferred. The first row of Table 24.5 displays the corresponding net values under the assumption that climate policy could be adjusted in the year 2035 to reflect the results of 30 years of research into the climate system that would produce a complete understanding of the climate sensitivity. In other words, the policy intervention would respond to new information in 2035 to follow a path that would then be optimal. The expected value of this responsive policy, computed now with our current understanding as depicted in Table 24.2, climbs to $117.82 billion (nearly a 22% increase), but the standard deviation also climbs to $90.11 billion (nearly a 21% increase in variance). Looking at Eq. (24.6) might suggest almost no change in the policy mix, as a result, but comparing the second rows of Tables 24.4 and 24.5 would support, instead, an increased emphasis on a climate-based intervention because the negative covariance of such a policy and possible climate-based outcomes has grown in magnitude (the relative value of climate policy has grown significantly in the upper tail of the climate sensitivity distribution). Notice, though, that these adjustments have little effect on the mean temperature increase; indeed, only the standard deviation seems to be affected.

Given the wide range of temperature change sustained by either "optimal" climate intervention, we now turn to exploring how best to design a Greenspan-inspired hedge against a critical threshold. If, to construct another example, a 3 °C warming were thought to define the boundary of intolerable climate impacts, then the simplified DICE framework under the median assumption of a 3 °C climate sensitivity would require a climate policy that restricted greenhouse gas concentrations to roughly 550 parts per million (in carbon dioxide equivalents). Adhering to a policy targeted at this concentration limit would, however, fall well short of guaranteeing that the 3 °C threshold would not be breached. As shown in the first row of Table 24.6, in fact, focusing climate policy on a concentration target of 550 ppm would produce only a distribution of temperature change across the full range of climate sensitivities with nearly 40% of the probability anchored above 3 °C. The associated discounted economic

Table 24.6 Exploring the economic value of a concentration-targeted climate policy contingent on climate sensitivity in the modified DICE environment.

Return in trillions of 1995$ and maximum temperature change in °C.

Climate sensitivity	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°	Mean	Standard deviation
Economic value	– 3.04	– 2.49	– 1.58	– 0.99	– 0.61	– 0.35	– 0.17	– 0.03	0.08	– 1.81	1.12
Max ΔT	1.83	2.31	3.00	3.45	3.79	4.06	4.29	4.48	4.65	2.86	0.96

Table 24.7 Exploring the economic value of the responsive temperature-targeted climate policy contingent on climate sensitivity in the modified DICE environment.

Return in trillions of 1995$ and maximum temperature change in °C.

Climate sensitivity	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°	Mean	Standard deviation
Economic value	– 0.01	– 0.81	– 1.58	– 1.03	– 0.56	– 0.25	– 0.02	0.13	0.24	– 0.54	0.60
Max ΔT	2.87	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.96	0.06

Table 24.8 Exploring the economic value of the responsive optimization after a temperature-targeted hedge contingent on climate sensitivity in the modified DICE environment.

Return in billions of 1995$.

Climate sensitivity	1.5°	2.0°	3.0°	4.0°	5.0°	6.0°	7.0°	8.0°	9.0°	Mean	Standard deviation
Economic value	0	35	114	165	205	249	270	296	311	106.15	106.19

values of this policy intervention (given the DICE calibration of damages) are recorded in the second row, and they are not very attractive. Indeed, the concentration target policy would produce a positive value only if the climate sensitivity turned out to be 9 °C and the expected value shows a cost of $1.807 trillion (with a standard deviation of more than $1.1 trillion).

Table 24.7 shows the comparable statistics for a responsive strategy of the sort described above; it focuses on temperature and not concentrations, so it operates closer to the impacts side of the climate system. In this case, the policy is adjusted in 2035 to an assumed complete understanding of the climate sensitivity so that the temperature increase is held below the 3 °C threshold (barely, in the case of a 9 °C climate sensitivity). In this case, the reduced damages associated with designing a policy tied more closely to impacts dominates the cost side and reduces the expected economic cost of the hedge to a more manageable $535 billion with a standard deviation of nearly $600 billion. Moreover, we know from the first section that beginning this sort of hedging strategy early not only reduces the cost of adjustment in 2035, but also preserves the possibility of meeting more restrictive temperature targets should they become warranted and the climate sensitivity turn out to be high.

Finally, Table 24.8 illustrates what would happen if it were determined in 2035 that the 3 °C temperature target was not required so that adjustment to an optimal deterministic policy would be best. Notice that hedging would, in this eventuality, produce non-negative economic value regardless of which climate sensitivity were discovered. Indeed, the mean economic value (discounted to 2005) exceeds $100 billion. Even though the variance around this estimate is high (caused in large measure because the value of the early hedging would be very large if a high climate sensitivity emerged), this is surely an attractive option.

24.5 Concluding remarks

The numerical results reported in Section 24.4 are surely model dependent, and they ignore many other sources of uncertainty that would have a bearing on setting near-term policy. They are not, however, the point of this paper. The point of this paper is that decisionmakers at a national level are already comfortable with approaching their decisions from a risk-management perspective. As a result, they should welcome climate policy to their arsenal of tools when they come to recognize climate change and its potential for abrupt and intolerable impacts as another source of stress and uncertainty with which they must cope. In this context, the numbers are important because they are evidence that currently available methods can provide the information that they need. Moreover, they are also important because they provide evidence from the climate arena to support the insight drawn from a manipulation of the Brainard framework (where uncertainty about the effect of policy is recognized) that doing nothing in the near term is as much of a policy decision as doing something.

Acknowledgements

I gratefully acknowledge the contributions and comments offered by participants at the 2004 Snowmass Workshop and two anonymous referees; their insights have improved the paper enormously. I would also like to highlight the extraordinary care in editing and the insightful contributions to content provided by Francisco de la Chesnaye; Paco's efforts were "above and beyond". Finally, the role played by William Brainard, my dissertation adviser at Yale, in supporting this and other work over the years cannot be overestimated – although I expect that Bill will be surprised to see his work on monetary policy cited in the climate literature. Remaining errors, of course, stay at home with me.

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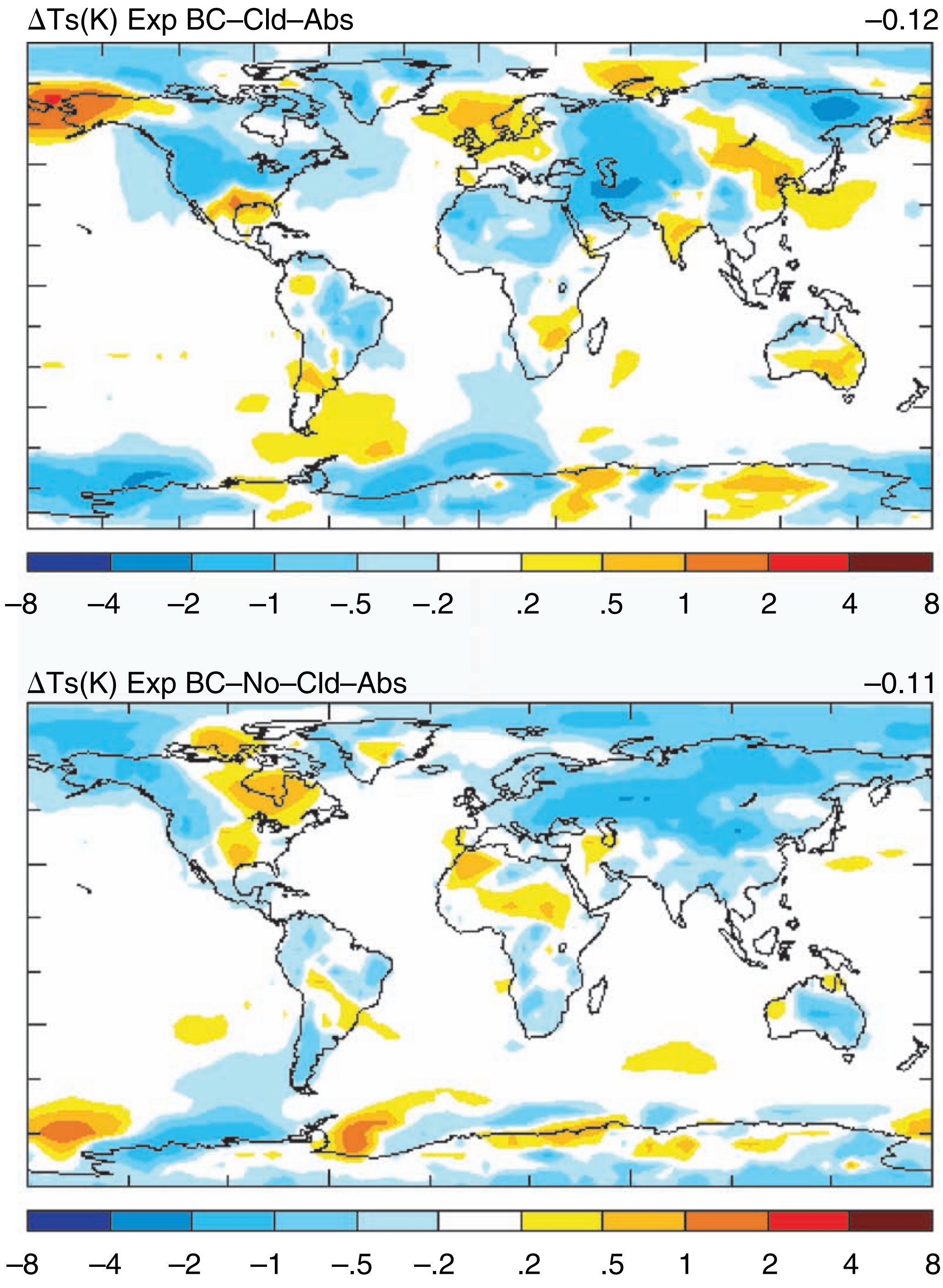

Figure 3.1 Model simulated annual surface temperature change (K) for year 2000 – Year 1850 for simulations that account for BC absorption in-cloud (top panel) and that do not account for BC (bottom panel).

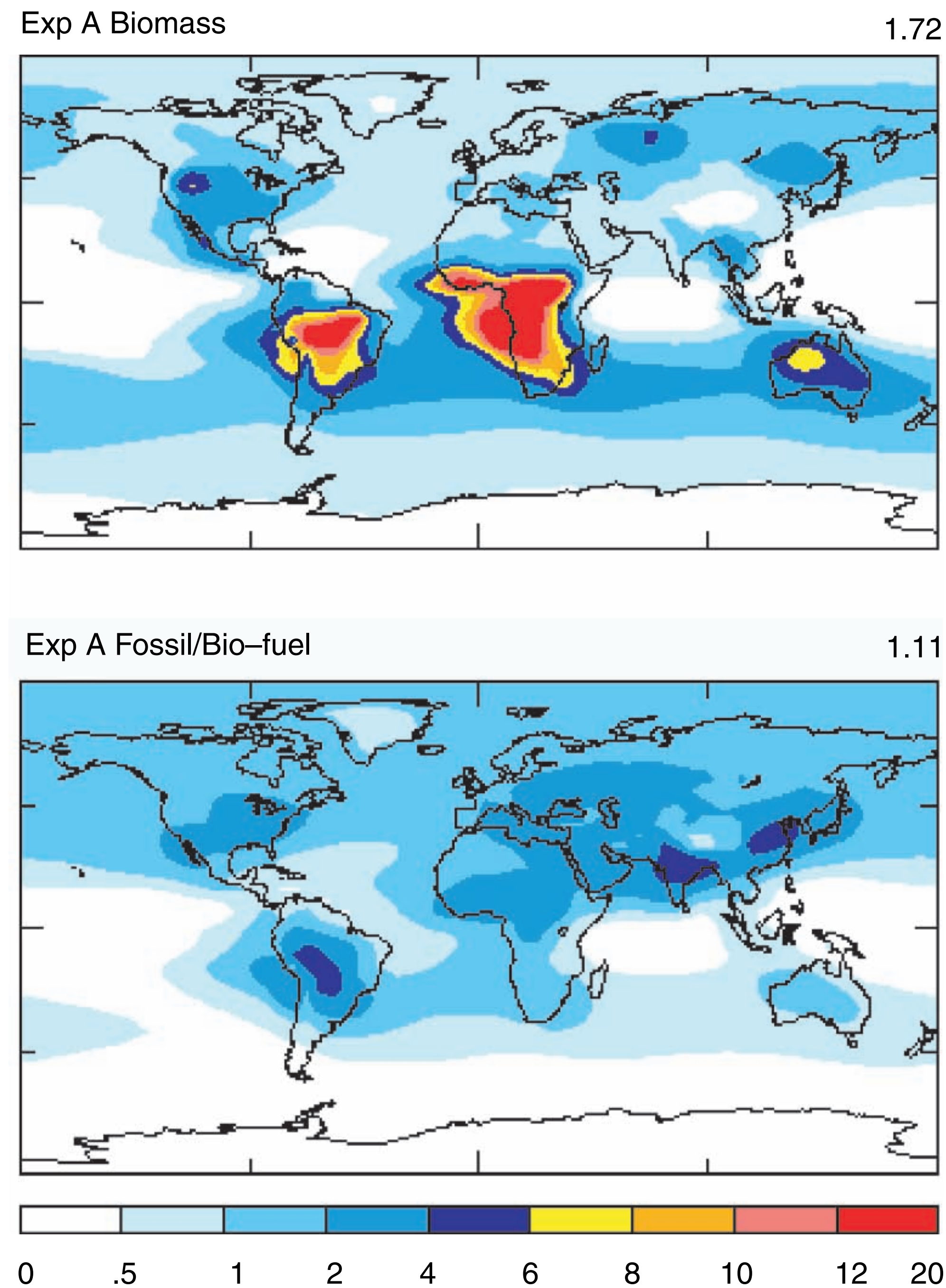

Figure 3.2 Annual values of carbonaceous aerosol column burden distribution (mg/m^2) from biomass (top panel and fossil- and biofuel sources (bottom panel). Global mean values are on the right-hand side of the figure.

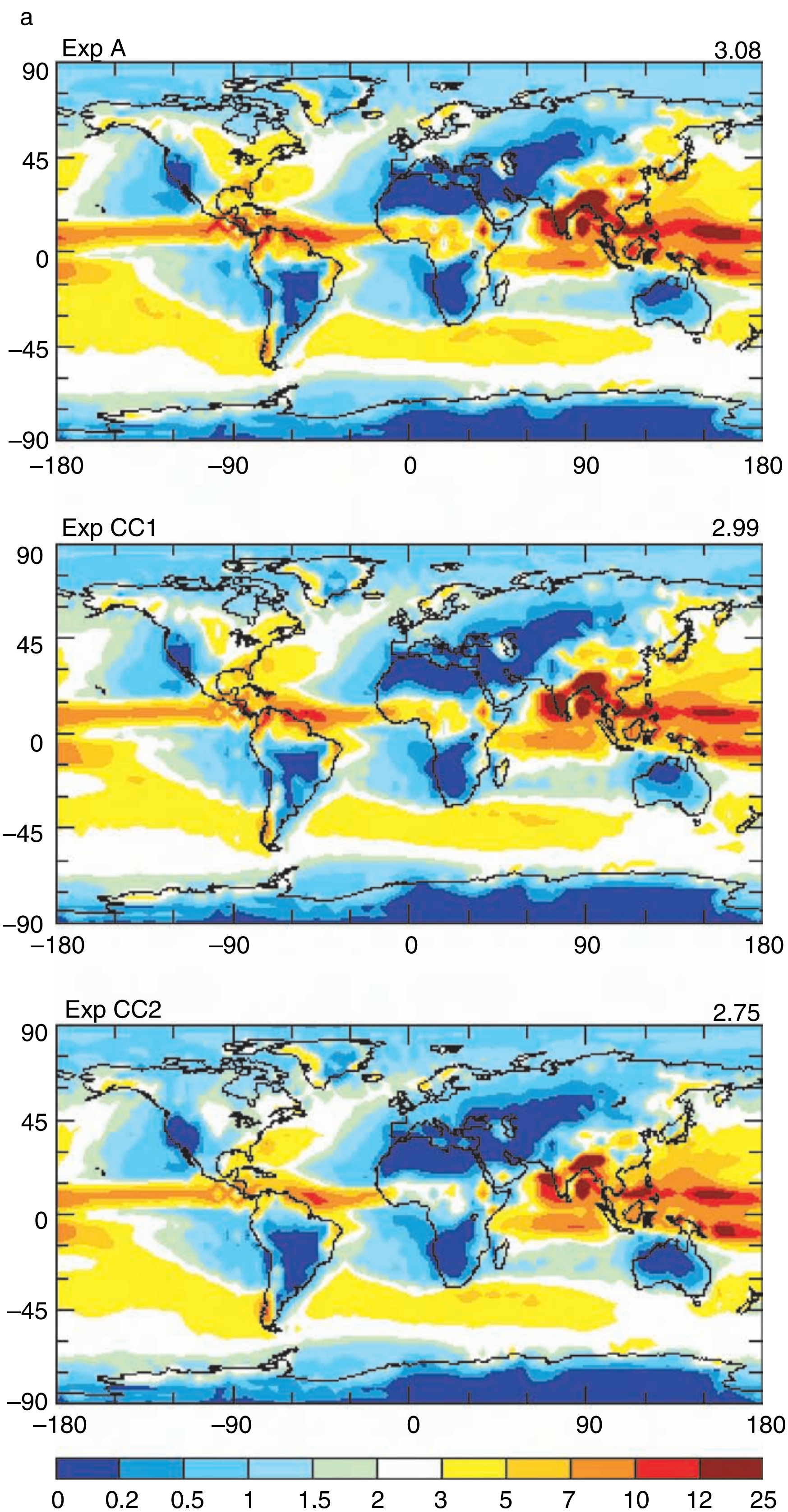

Figure 3.3 Continued

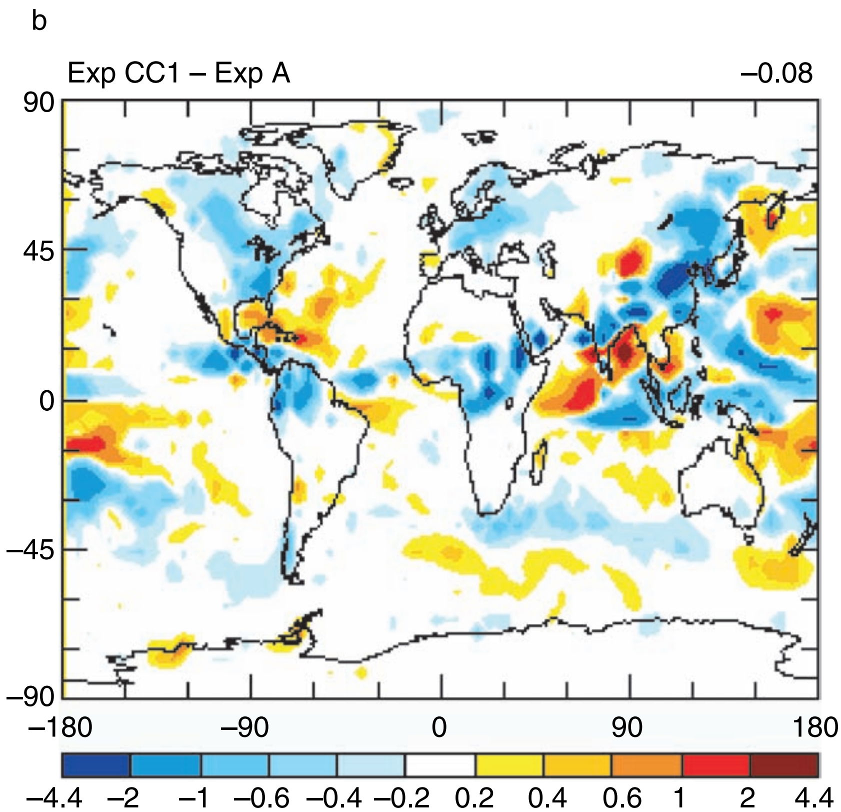

Figure 3.3 June–July–August precipitation (mm/day) fields for the year 2000 from Exp A, Exp CC1 and Exp CC2 (a), and change in precipitation between Exp CC1 and Exp A (b). Global mean values are indicated on the right-hand side.

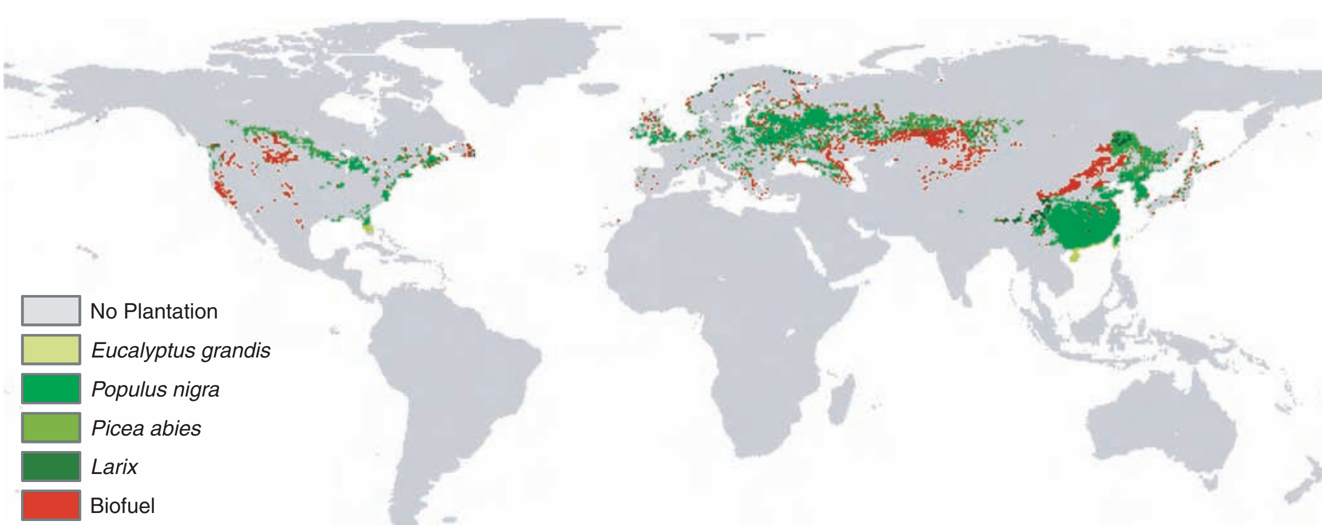

Figure 6.2 Carbon-plantation tree types for the year 2100 in the IM-C experiment. Because of the extra surplus-NPP constraint on C-plantations and bioclimatic limits, the total area of these is smaller than that of biomass plantations. The additional area of biomass plantations in the IM-bio experiment is indicated in red. Land-cover changes for regions other than the northern hemisphere regions selected for the sensitivity experiments in this paper are not shown here.

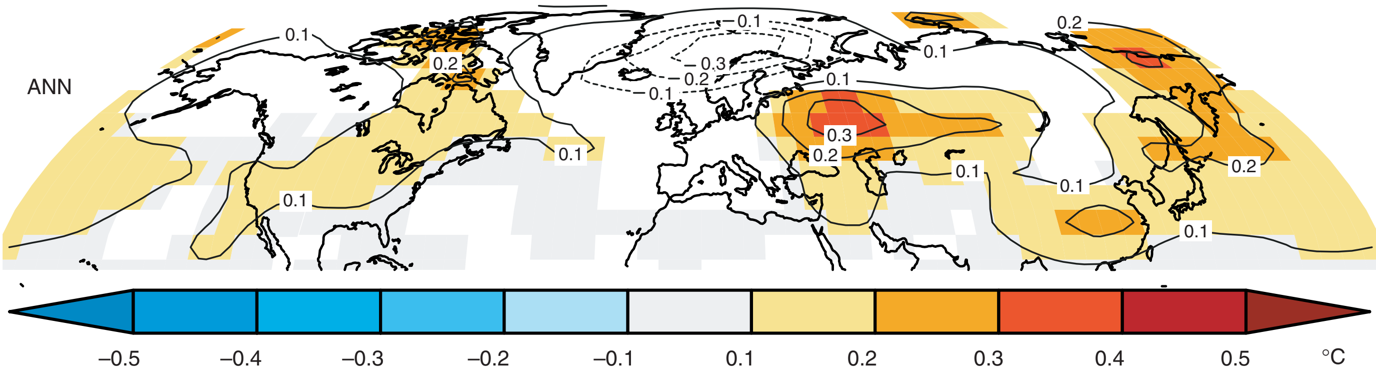

Figure 6.8 Difference in annual-mean surface-air temperature in 2071–2100 (°C) of carbon-plantation with respect to biomass-plantation ensemble mean, including albedo effects. Contours are plotted for all model grid cells. Colored are the grid cells for which the difference between the two ensemble means is significant above the 95% level (2-tailed *t*-test).

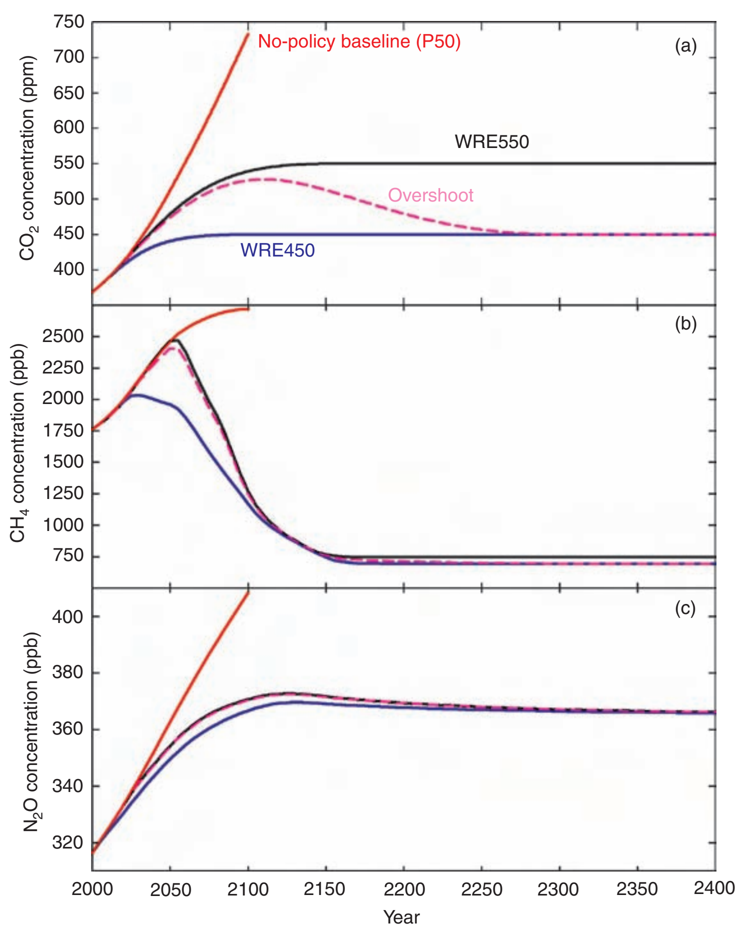

Figure 7.1 (a) Revised WRE and a new overshoot concentration stabilization profile for CO_2 compared with the baseline (P50) no-climate-policy scenario. (b) Methane concentrations based on cost-effective emissions reductions (Manne and Richels, 2001) corresponding to the WRE450, WRE550, and overshoot profiles for CO_2. The baseline (P50) no-climate-policy scenario result is shown for comparison. (c) Nitrous oxide concentrations based on cost-effective emissions reductions (Manne and Richels, 2001) corresponding to the WRE450, WRE550, and overshoot profiles for CO_2. The baseline (P50) no-climate-policy scenario result is shown for comparison.

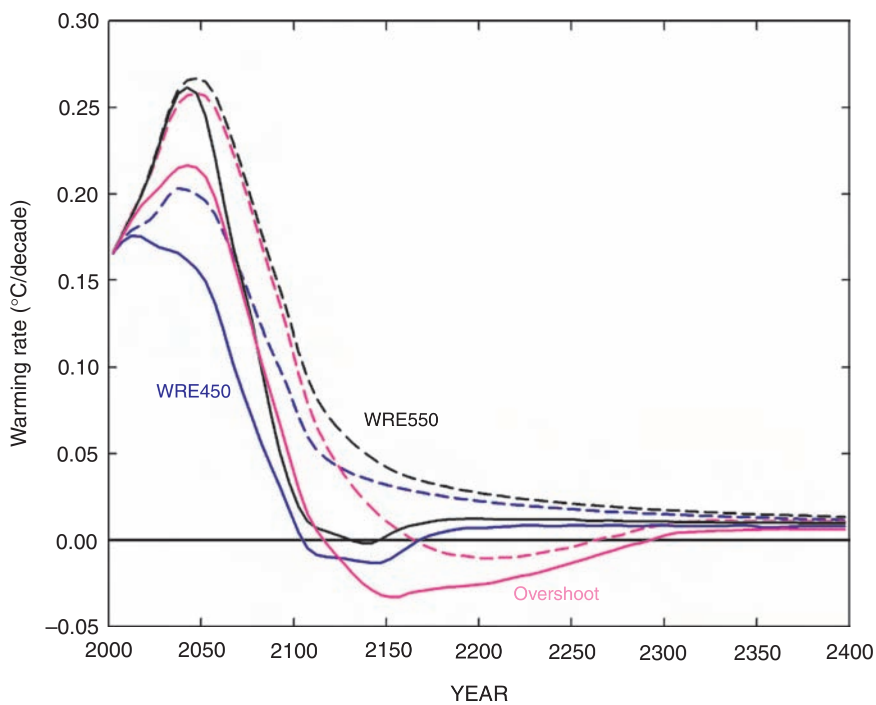

Figure 7.4 Rates of change of global-mean temperature (°C/decade) for the temperature projections shown in Figure 7.3a.

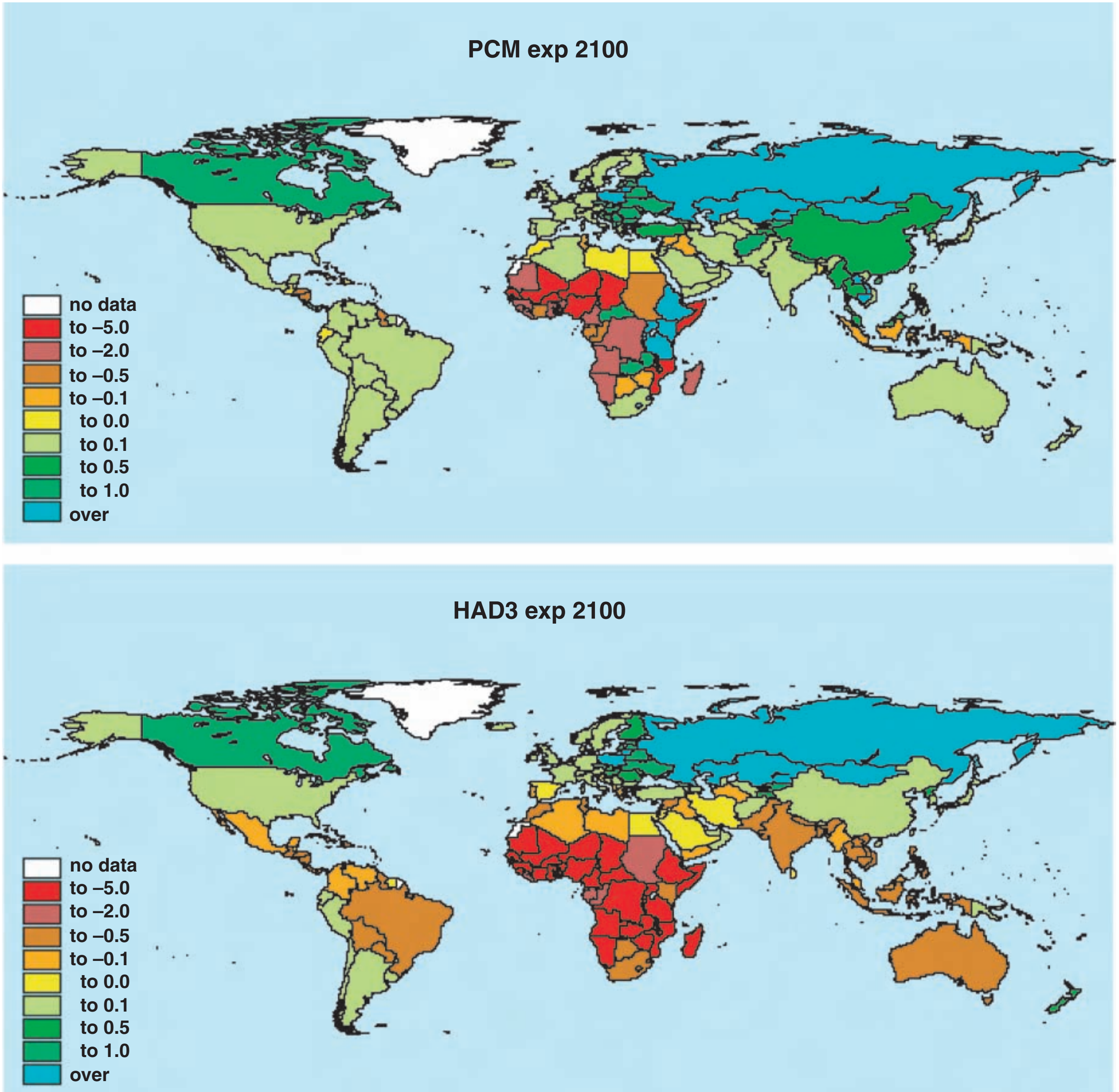

Figure 9.8 Aggregate impacts (percent change in GDP) in 2100.

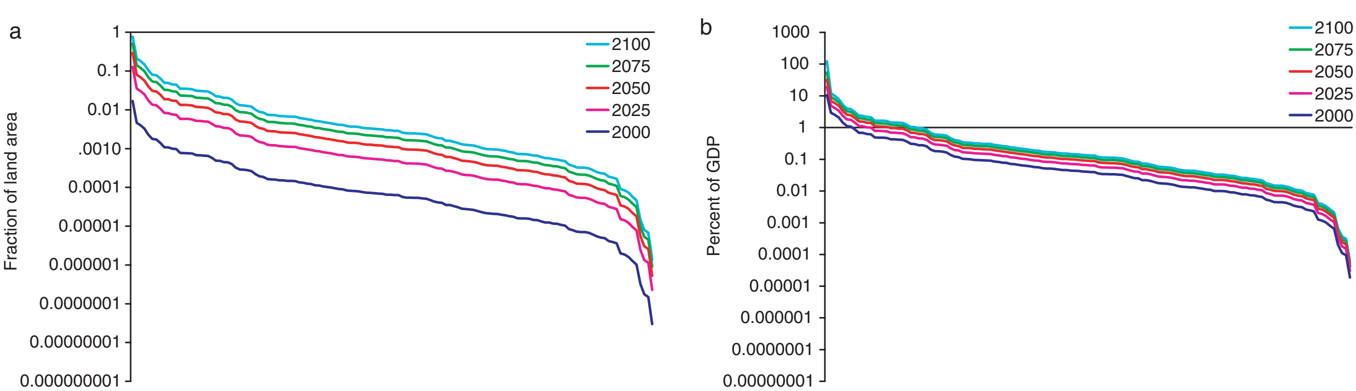

Figure 10.3 Loss of dryland (fraction of total area in 2000; panel(a)) and its value (percentage of GDP; panel(b)) without protection. Countries are ranked as to their values in 2100.

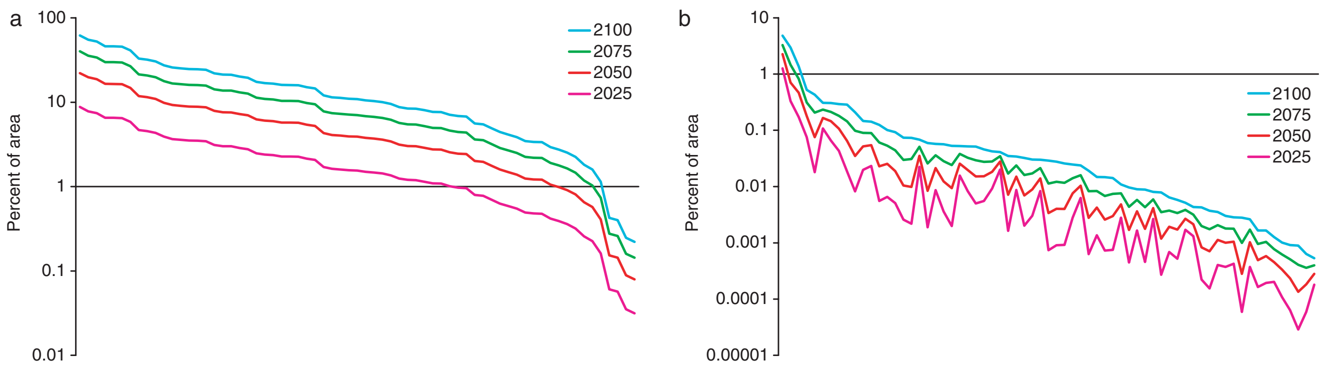

Figure 10.4 Loss of wetland (fraction of total area in 2000; panel(a)) and its value (percentage of GDP; panel(b)) without protection (left panels). Countries are ranked as to their values in 2100.

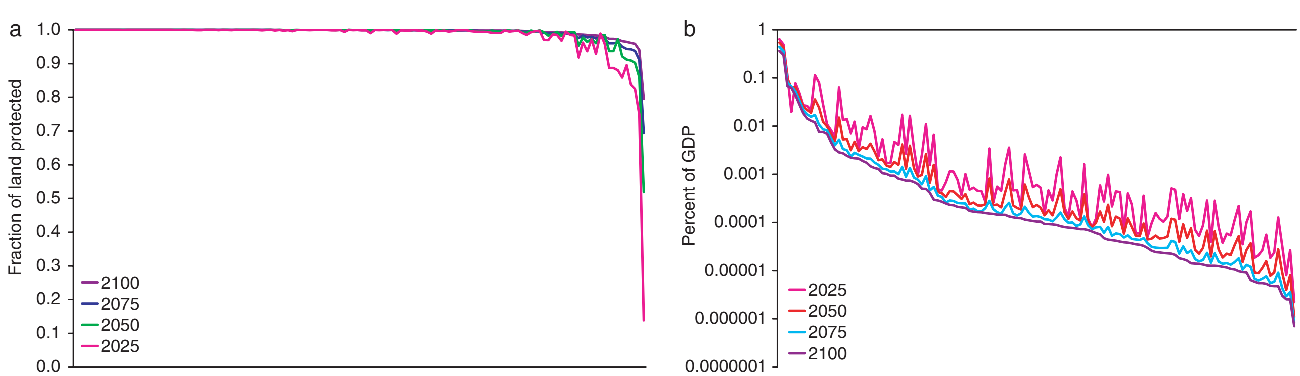

Figure 10.5 Protection level (fraction of coast protected; left panel) and the costs of protection (percent of GDP; right panel). Countries are ranked as to their protection level.

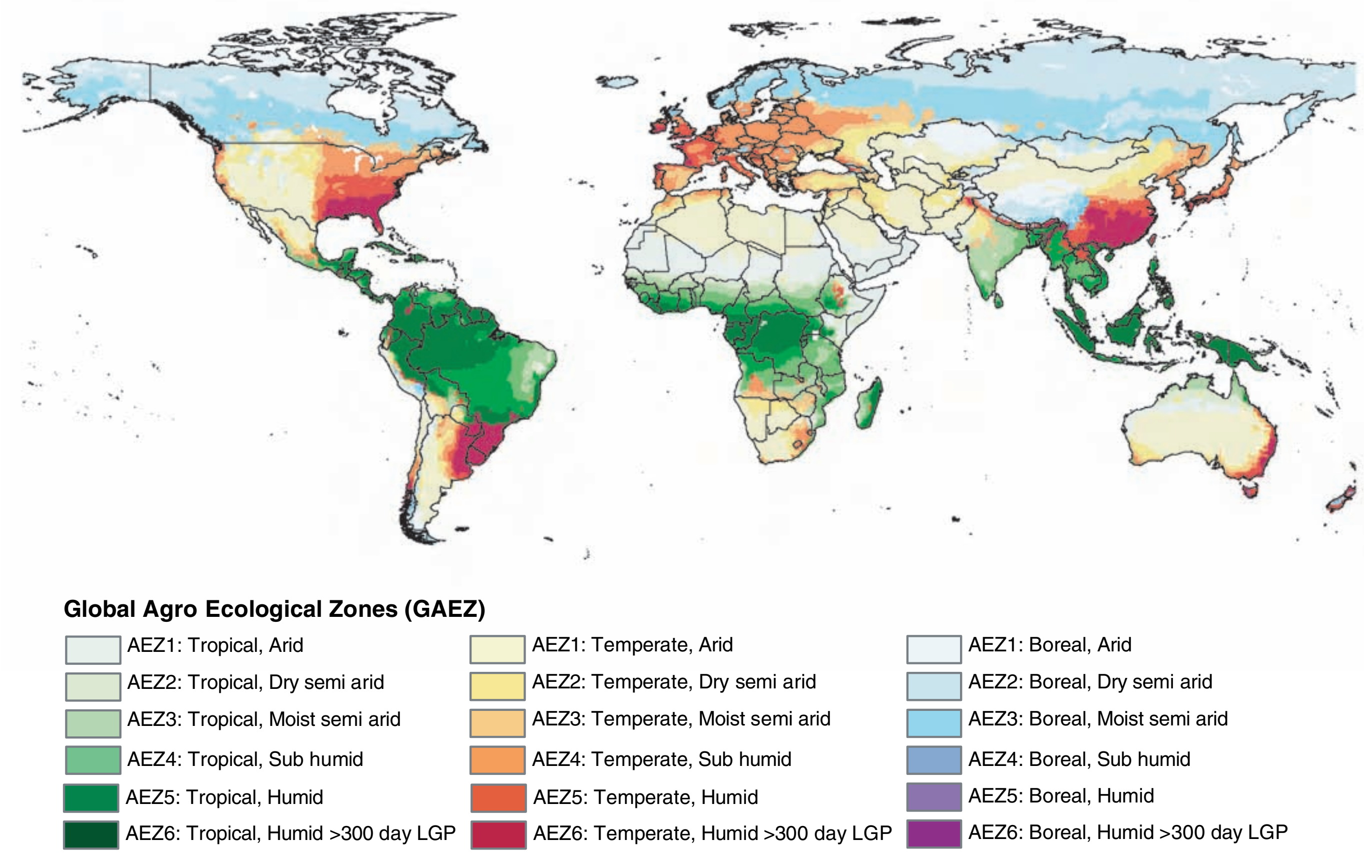

Figure 21.2 The global distribution of global agro-ecological zones (AEZ) from this study, derived by overlaying a global data set of length of growing periods (LGP) over a global map of climatic zones. LGPs in green shading are in tropical climatic zones, LGPs in yellow-to-red shading lie in temperate zones, while LGPs in blue-to-purple lie in boreal zones. LGPs increase as we move from lighter to dark shades.

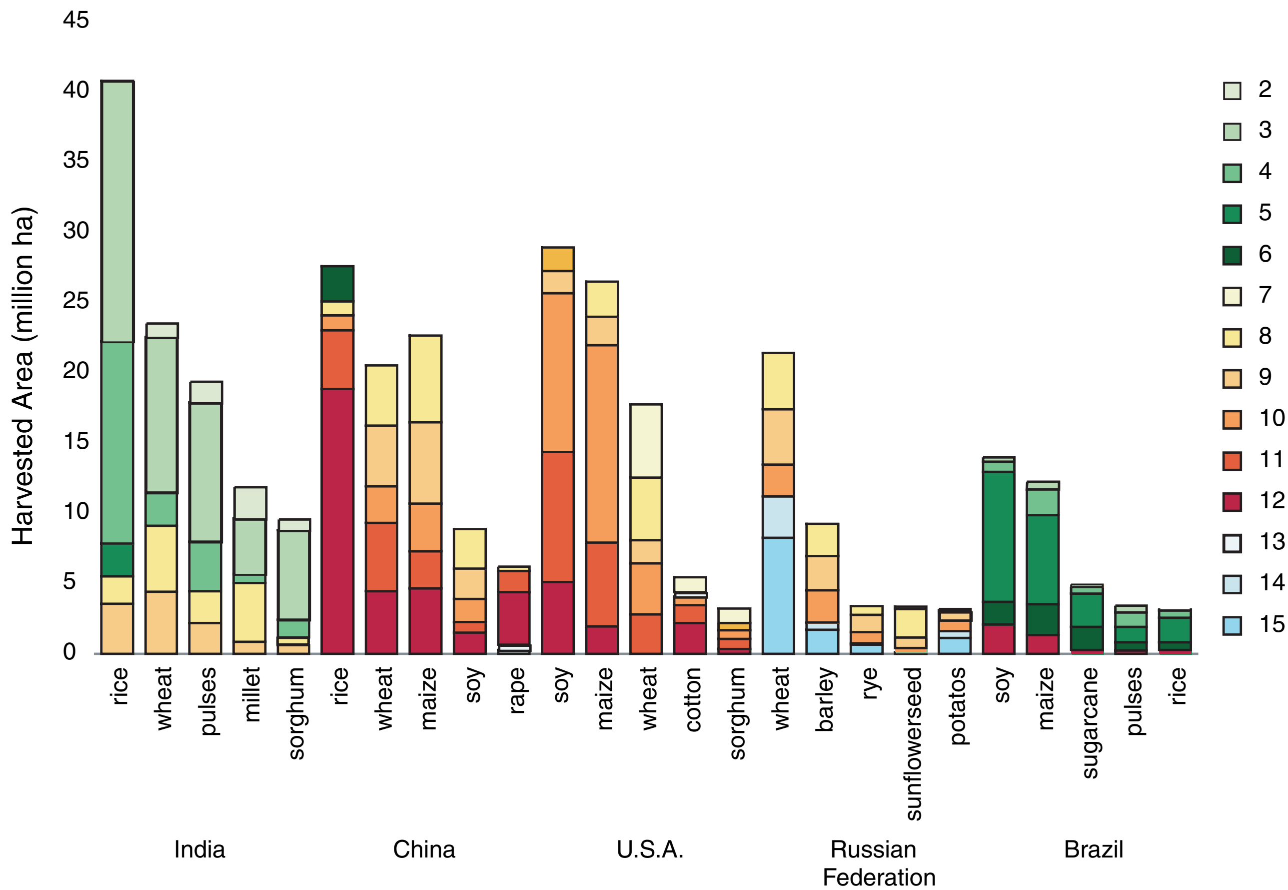

Figure 21.5 The top five nations of the world, in terms of total harvested area, the top five crops and their harvested areas within each nation, and the AEZs they are grown in. Tropical AEZs are shown in green, temperate in yellow-to-red, and boreal in blue-to-purple.

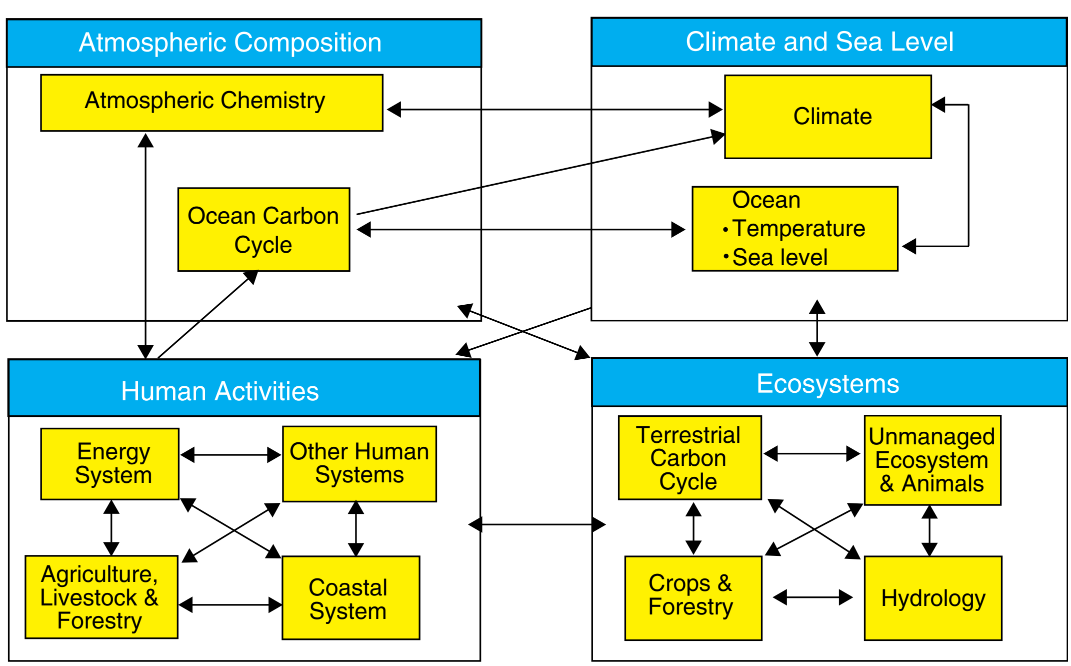

Figure 31.1 A schematic diagram of the major components of a climate-oriented integrated assessment model.

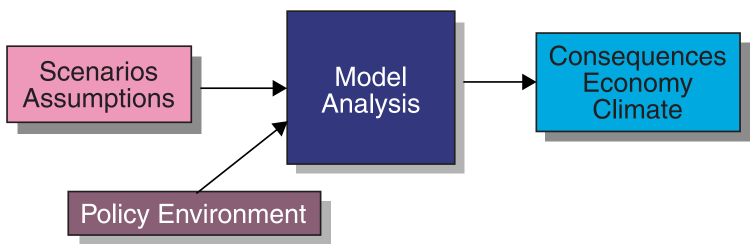

Figure 31.2 A schematic diagram of the elements of an IA model-based policy process.