Global Climate Change and Extreme Weather: An Exploration of Scientific Uncertainty and the Economics of Insurance

L. James Valverde, Jr.   Marcellus W. Andrews

Insurance Information Institute
New York, USA

1. Introduction

Current efforts to confront the prospect of anthropogenic climate change present policymakers and intergovernmental negotiators with a host of challenges. The technically-intensive nature of the policy debates that surround this issue are complex and multifaceted. Indeed, much of the uncertainty that underlies the greenhouse debate arises, in part, from an incomplete understanding of atmospheric and climate science. [1] Even a cursory read of the day's newspapers reveals that climatic change is likely to impact society in ways that are, perhaps, only just beginning to be understood.

Nowhere, it seems, does this sentiment ring more true than for American insurers and reinsurers. As a key instrument and enabler of loss mitigation and risk transfer, the U.S. insurance industry lies at the nexus of several crucial dimensions of the climate change problem, especially as it relates to the potential implications of climate change for society and the global economy. Having sustained record-breaking natural catastrophe losses, insurers and reinsurers are openly — and, indeed, justifiably — questioning the potential linkage between anthropogenic climate change and extreme weather, looking at both the likely short-term implications for the industry, as well as potential long-term impacts on financial performance and corporate sustainability. [2]

[1] The sources of scientific uncertainty within this debate are many. For example, difficulties in predicting future levels of anthropogenic emissions of key greenhouse gases and their effects on the global carbon cycle make it difficult to reliably assess the potential *magnitude* and *impacts* of global climate change. The climate change problem is, in addition, characterized by several unique features, all of which complicate efforts to arrive at reasoned responses to the prospect of anthropogenic global warming. For example, the time horizons that must be considered in the evaluation of climate change response strategies are on the order of one or more centuries. And although the climate change problem is global in scale, the spatial and temporal distribution of impacts is likely to be non-uniform. Moreover, the physical inertias that drive the global climate system are such that the potential social-economic and environmental impacts associated with climatic change are, to varying degrees, irreversible.

[2] In truth, interest in this topic within the industry dates as far back as the late 1980s, with the appearance of Hurricane

Situated at the very heart of these discussions, of course, are the scientific debates that surround the issue of global climate change. Prudent insurers will pay close attention to these debates for at least three reasons. First, they will want to know the full range of informed opinion that exists as to how the Earth's climate is changing, as well as the potential consequences of such change for a broad range of possible (re)insurance-related outcomes. Second, insurers will want to take note of the balance of scientific opinion on these matters so that they can make informed choices about other (perhaps non-weather-related) risks they underwrite that could be affected by climatic change — perhaps in ways that are not yet well understood. Third, insurers will also be concerned about the accumulation of large natural catastrophe losses with potentially significant, but uncorrelated, losses such as terrorism. While the probabilities associated with such uncorrelated events are independent, the financial ability to pay claims in the wake of either type of loss is not.

Insurance in an age of global climate change is, in essence, a dual gamble. In the first instance, the gamble is one that sees insurers and reinsurers engaged in the process of making a series of (partially) informed bets on the potential *frequency*, *severity*, and *consequences* of natural catastrophe events — a task that is, in itself, fraught with uncertainty. In the second instance, though, global climate change holds the potential to, in effect, confound our current understanding of the causes and consequences of extreme weather events. If this portion of the dual gamble yields unfavorable outcomes for insurers, then it may signal the need for potentially drastic shifts in the way these risks are construed, assessed, and managed.

The prospect of anthropogenic climate change has potentially far-reaching implications for the insurance and reinsurance industries. Depending on how these risks are perceived by individual players within the industry, there exists a broad range of possible response options. In the best of all possible worlds, for example, insurers can opt to assume that the future will look much like the past. In this "business-as-usual" scenario, insurers go about their business of managing risk in ways that are largely consistent with what they have traditionally done in the past. Under this mindset, traditional paradigms and methods are deemed sufficient to adequately assess and manage these risks. However, what if insured natural catastrophe losses continue to mount in ways that continue to surprise decision-makers and elude reliable forecasting? Faced with this situation, insurers may choose to direct more effort and resources at (i) better appraising these risks; and (ii) better managing their relevant exposure levels. This course of action, of course, proceeds from an almost axiomatically accepted doctrine within the industry, namely, that the risks in question can be reliably appraised using the language of probability and statistics. The global climate system is, however, fundamentally *chaotic* in nature, which may sharply limit the reliability of short- to medium-term extreme weather forecasts, as

---

Gilbert in 1988. In addition to the insured losses arising from Hurricane Gilbert, interest in climate change was also spurred by signals from the scientific community that hurricane activity in the North Atlantic was possibly being influenced by anthropogenic warming. In 1988, for example, the American Meteorological Society issued a policy statement postulating that greenhouse warming would, in the long run, lead to "a higher frequency and greater intensity of hurricanes" [3]. Recent efforts to explore this topic include refs. [2] and [32].

well as inhibit the precise estimation of key weather-related factors (e.g., humidity, precipitation, atmospheric and sea-surface temperature, and wind activity).

As we discuss at length below, the highly uncertain state of scientific knowledge concerning the potential linkage between climate change and extreme weather does not allow us to say much that is definitive or certain. And while insurers and reinsurers are well-accustomed to confronting situations that are characterized by risk and uncertainty, the issue of anthropogenic climate change carries with it enough ambiguity and uncertainty that it generates considerable anxiety for industry stakeholders. In essence, the problem stems from the fact that while insurers and underwriters are often able to reach requisite levels of comfort in situations where the attendant risks can be reliably characterized and appraised, they are far less comfortable in situations where scientific uncertainty complicates a decision-making environment that is already fraught with uncertainty and complexity. Of course, complicating matters further is the fact that all of this plays out in an environment where it is often difficult to parse and disentangle the political rhetoric and considerations that inevitably become part of the dialogue on how the global environment should be managed.

A fundamental question that we pose here, then, is whether the risks posed by global climate change are, in some way, *structurally* different than what has previously come to pass, thereby presenting insurers with new — and, some would argue, unprecedented — challenges, requiring a fundamental rethinking of the mindsets and methods that are used to manage these risks. Indeed, it may be the case that traditional underwriting and risk management methods are not adequate for this task. In this regard, three issues are seen to be central:

- To what degree can the *scientific uncertainty* underlying the climate change and extreme weather problem be reliably characterized and evaluated by insurers and reinsurers?

- To what degree does the global climate system itself hold the potential for *surprise* to decision-makers?

- How *resilient* is the system to these shocks, and what actions might insurers and reinsurers take to minimize the effects of these shocks?

In what follows, we take up these questions in the context of the potential linkage that may exist between anthropogenic climate change and extreme weather, with particular emphasis on tropical cyclone activity in the North Atlantic. Our remarks are organized along the following lines. We begin, in Section 2, with an overview of key aspects of climate science, together with a discussion of the various approaches that scientists currently use to model various features of the global climate system. With this as background, Section 3 summarizes and appraises the best available scientific evidence on the potential linkage between global climate change and extreme weather. As part of this discussion, we explore both empirical and theoretical insights concerning efforts to produce reliable projections of future changes in tropical cyclone activity. We close this section with a discussion of issues pertaining to storm vulnerability and exposure, especially in coastal areas. Section 4 then explores the resilience of the property/casualty (P/C) industry to extreme weather events. In particular, we explore the profitability consequences of massive losses from one exemplary form of extreme weather — a string of storms like those striking the U.S. in 2004 (hereafter referred to as "Quartet-scale storms"), as well as the prospect of a Katrina-scale storm combined with a mass terror attack on the scale of 9/11 — on the theory that prudence in the face of scientific uncertainty warrants consideration of a few worst-case scenarios. The results of this econometric exercise suggest a high degree of macro-resilience for the insurance industry in the limited sense that the system, with its current operating procedures, can withstand a series of extreme weather shocks. We conclude, in Section 5, with a closing commentary on these issues, where we discuss some of the long-term challenges the P/C industry is likely to face on matters pertaining to global climate change.

2. The Scientific Basis for Climate Change

The history of scientific study of climate change is longer than most people realize. More than a century ago, for example, Fourier [14] was the first to notice that the Earth is a greenhouse, kept warm by an atmosphere that reduces the loss of infrared radiation. The overriding importance of water vapor as a greenhouse gas was recognized even then. In the late 1890s, Arrhenius [4] was the first to quantitatively relate the concentration of carbon dioxide (CO_2) in the atmosphere to global surface temperature. Given this long-standing history, one might lament the fact that — perhaps owing, in part, to the politically-charged nature of the topic — many people mistakenly assume that the science that underlies our current understanding of climatic change is, in some way, suspect or unreliable. Of course, the nature of the greenhouse debate is far too complex and multifaceted to lend itself well to simplistic “is it happening or isn’t it?” characterizations. In what follows, we explore various key features of the scientific basis for climate change, together with various analytical efforts directed at modeling the core elements of the global climate system.

The Natural Greenhouse Effect

The global climate system is comprised of several major components, all of which interact with one another in complex and often unpredictable ways. The fundamental process that drives the climate system is *heating* by incoming short-wave radiation and *cooling* by long-wave radiation into space. In general, the climate system of the Earth can be seen to consist of five basic components:

- **Atmosphere**. Absorbs and emits infrared radiation; clouds promote cooling by reflecting sunlight.

- **Oceans**. Exert a large influence on current climate conditions; absorb over half of the solar radiation reaching the Earth’s surface. The heat capacity of the ocean delays the response of the climate system.

- **Land**. Atmospheric processes are strongly coupled to the land surface of the planet. The soil interacts with the atmosphere via exchanges of aerosols, gases, and moisture. Such exchanges are influenced by soil type and vegetation, and are strongly dependent on soil wetness.

- **Ice**. Reflects sunlight; sea-ice reduces heat exchange between the ocean and atmosphere, and affects climate on time-scales of seasons and longer.

- **Biosphere**. Affects climate by influencing atmospheric composition, albedo,[3] and hydrology. Also controls the magnitude of the fluxes of several greenhouse gases (GHGs), including CO_2 and methane.

These basic components of the global climate system are depicted in Figure 1.

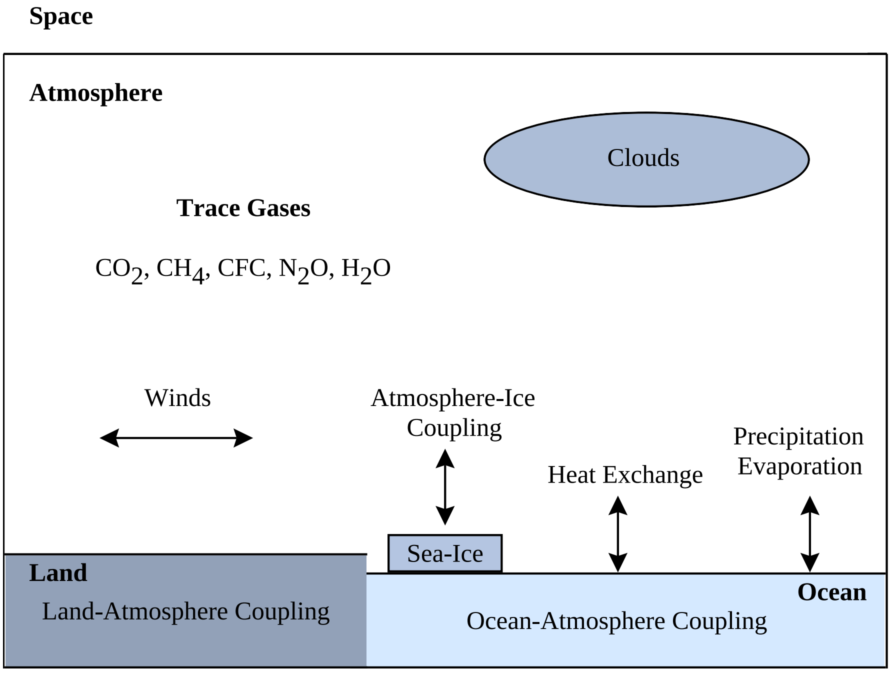

Fig. 1. Simplified representation of the global climate system.

The Earth's climate is largely influenced by changes in *radiative forcing*[4] that arise from changes in the concentrations of radiatively-active gases in the troposphere and the stratosphere.[5] As Figure 2 illustrates, the global climate system is driven primarily by incoming solar radiation. On an annually-averaged global scale, roughly one-third of the incoming solar radiation is reflected back out into space. Some of the outgoing (infrared) radiation is partially absorbed, and is then re-emitted by naturally-occurring GHGs. This so-called *natural greenhouse effect* warms the surface temperature of the Earth by approximately 33°C more than it would otherwise be if naturally-occurring GHGs were not present. The remaining two-thirds of the incoming radiation is absorbed by the atmosphere, land, ice, and ocean surfaces.

[3] *Albedo* is defined as the ratio of reflected to incident radiation, and provides a measure of the *reflectivity* of the earth's surface and its atmosphere.

[4] *Radiative forcing* is formally defined as a change in the *average net radiation* at the tropopause — the region between the troposphere and the stratosphere — brought about by changes in either the incoming solar radiation, or in the outgoing infrared radiation. Radiative forcing therefore disturbs the balance that exists between incoming and outgoing radiation. As the climate system evolves over time, it responds to the perturbation by slowly re-establishing the radiative balance. In general, positive radiative forcing tends (on average) to give rise to surface warming, whereas negative forcing tends (on average) to give rise to surface cooling.

[5] The troposphere is the lowest region of the atmosphere, and the stratosphere is the zone of the atmosphere above the troposphere.

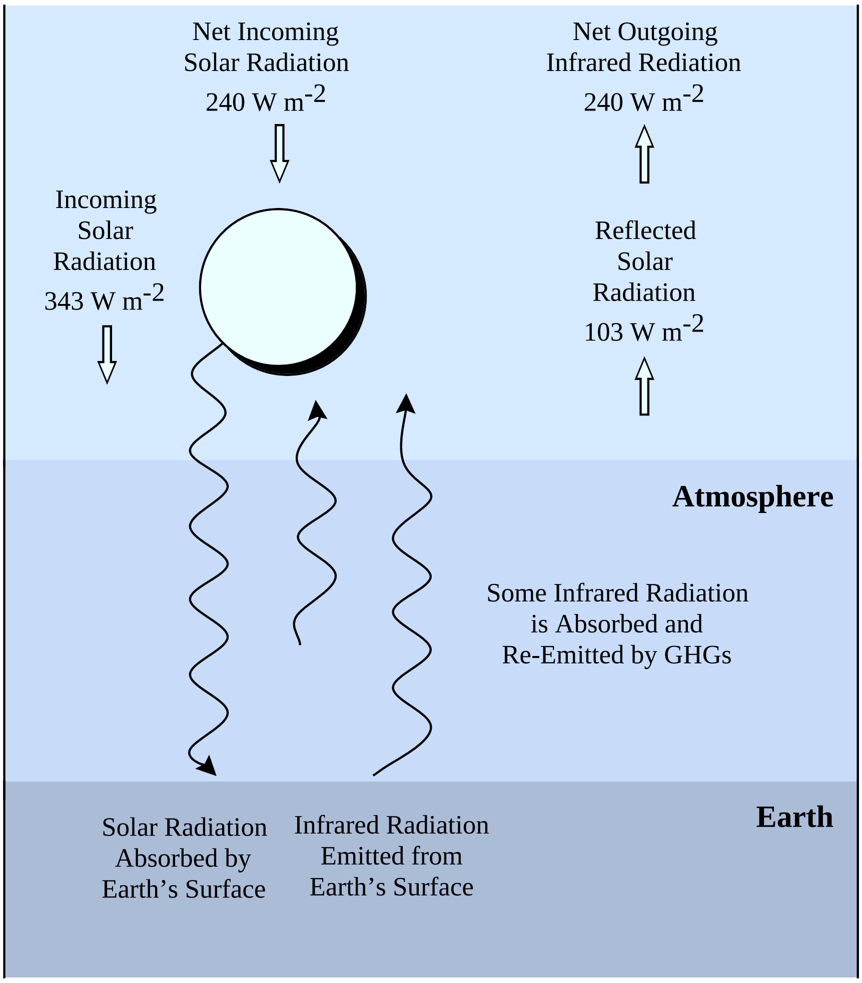

Fig. 2. Schematic representation of the global long-term radiative balance of the Earth's atmosphere.

In Figure 2, the solar radiation that is absorbed by the Earth's atmosphere and surface is — in the long run — balanced by the outgoing infrared radiation. In equilibrium, the absorbed solar energy is balanced by the radiation that is emitted to space by the planet surface and the atmosphere. Any factor that disturbs this balance is called a *radiative forcing agent* [21].

The Centrality of CO_2

Carbon dioxide is the most important anthropogenic GHG, largely due to the fact that its emissions are directly influenced by human activities. Indeed, long-term predictions of anthropogenic emissions of key GHGs play a central role in current efforts to obtain reliable predictions of future concentrations of radiatively and chemically important trace species in the Earth's atmosphere. Understanding the sources of the long-lived gases — CO_2, methane (CH_4), nitrous oxide (N_2O), and chlorofluorocarbons (CFCs) — is central to assessing changes in radiative forcing that will ultimately influence climatic change in the future. [6]

Ignoring the uncertain effects of the CFCs and changes in ozone, increases in CO_2 have, to date, contributed to roughly 70% of the enhanced greenhouse effect, with methane (CH_4) and nitrous oxide (N_2O) accounting for the remaining $\sim 23\%$ and $\sim 7\%$, respectively. Carbon dioxide is therefore likely to play a dominant role in future warming, whereas, over the course of the next century, the role of the other key GHGs is expected to be relatively minor. [7]

GHGs are typically classified in terms of their levels of *concentration* in the atmosphere, and in terms of the strength of their absorption of infrared radiation. Since pre-industrial times, CO_2 levels in the atmosphere have increased by more than 25%, from approximately 280 ppmv [8] to approximately 356 ppmv [5]. At present levels of atmospheric CO_2 concentrations, the relation between changes in the current GHG concentration levels and radiative forcing is strongly nonlinear [5]. This relation is typically expressed in terms of changes in *net radiative flux* at the tropopause (i.e., the top of the troposphere). In formal terms, these changes are represented as

$$\Delta F(t) = f\ \Big(\ C(t_0),\ C(t)\ \Big),$$

where $\Delta F(t)$ denotes the change in net flux measured in Watts per square meter (Wm^{-2}) corresponding to a volumetric concentration change from the initial concentration level at time period t_0 to the concentration level at some later time period t.

Climate modelers utilize detailed radiative transfer models to explore the relationships that exist between radiative forcing and the levels of atmospheric concentration of key GHGs. These radiative transfer models simulate the variation of the absorption and emission for specific GHGs, as a function of wavelength. [9]

The concentration-forcing relationships that are derived from radiative transfer models are typically characterized by complicated functional forms. These complex representations can, however, be used to derive simpler analytical expressions. For carbon dioxide, the functional form of f is well approximated by presuming a logarithmic dependence of $\Delta F(t)$ on $C(t)$. Specifically,

[6] Because of their influence on atmospheric chemistry, emissions of several short-lived gases — such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon monoxide (CO) — are also important.

[7] Long-term projections of non-CO_2 GHGs are, at present, highly uncertain. Given this consideration, together with those outlined above, it is common practice to take these other gases and convert them to equivalent amounts of CO_2. These so-called *CO_2-equivalents* represent the amounts of CO_2 that would give rise to the same radiative forcing.

[8] 1 ppmv $\equiv$ 1 part per million by volume.

[9] These models also account for any overlap that exists between the absorption bands of the gases, as well as for the effects that clouds have on radiative transfer [21].

$$\Delta F(t) = 6.3 \ln \left(\frac{C(t)}{C(t_0)} \right), \tag{1}$$

where $C(t_0)$ and $C(t)$ are the atmospheric concentrations of CO_2 in ppmv at times t_0 and t, respectively. [10]

It is worth noting that the uncertainty that underlies the specification of the CO_2 concentration-forcing relationship arises from several sources. First, the radiative transfer models that are used to derive the complicated functional forms that ultimately give rise to Eq. (1) are themselves uncertain. For example, Shine et al. [40] cite a 1984 study that places the uncertainties at around $\pm 10\%$.

In a more recent study, Cess et al. [8] document the uncertainties in carbon dioxide radiative forcing in 15 general circulation models (GCMs) — by far the most sophisticated tools for performing global climate simulations. A series of CO_2 doubling experiments revealed substantial differences among the 15 models. [11] In their efforts to arrive at a comparative understanding of the scientific differences and similarities in these 15 GCMs, Cess et al. found that the largest contributor to the observed model-to-model variations was the carbon dioxide radiation parameterizations used in the GCMs. In addition, they found that the models used in the study gave a global warming average of approximately $4°$C, and produced an average CO_2 forcing of 4.0 Wm^{-2}. These results are equivalent to an average climate sensitivity of 1°C of warming for each 1 Wm^{-2} of radiative forcing.

In discussing the implications of this finding, Cess et al. make the following observation: Imagine that the 15 GCMs used in the study possess the same climate sensitivity of 1°C warming per 1 Wm^{-2} and, in addition, possess the same observed forcing variation. Under this set of assumptions, for presumed CO_2 concentration levels, the global warming projections given by the 15 GCMs would range from 3.4°C to 4.7°C *just because of their forcing differences*. This is an important observation, in that the range is substantial and, moreover, constitutes nearly half of the often-quoted Intergovernmental Panel on Climte Change (IPCC) climate sensitivity range of 1.5° – 4.5°C. We note that the IPCC range is based only on *feedback uncertainties*, and assumes no differences in the forcing. Also, the 3.4°C lower-bound specified by Cess et al. is well above the IPCC "best estimate" of 2.5°C. Findings such as this provide an initial basis for explaining the degree of scientific uncertainty that surrounds current climate sensitivity estimates. [12]

[10] Equation (1) yields reasonable approximations of CO_2-induced radiative forcing for values of $C(t)$ less than 1000 ppmv.

[11] In accounting for these differences, Cess et al. suggest several hypotheses: (i) Differences in the lapse rate among the models; (ii) Differences in the atmospheric water vapor distributions among the models; (iii) Differences in the parameterization of radioactive overlap in the radiation codes of the models; and (iv) Differences in the GCM cloud fields.

[12] For a discussion concerning the range of scientific opinion about climate sensitivity, as well as other key climate-change-related quantities, see, e.g., Morgan and Keith [33].

Modeling the components and processes that, together, make up the global climate system is a complicated task. Numerical models attempt to mimic or simulate the physical processes that give rise to climatic change. In order to simulate the dynamic behavior of the climate system, modelers utilize simplified representations, most of which are based on physical laws governing such factors as mass, momentum, and energy flows and exchanges in the atmosphere.

The task of arriving at realistic representations of the global climate system's main components and processes is complicated by a number of factors. First, many of the physical laws that govern the processes that influence climate change are poorly understood. [13]

The uncertainties that underlie modern atmospheric science's best physical representations of clouds and oceans limit the predictive capability of even the most sophisticated climate models. Most climate models are extremely sensitive to the manner in which clouds are represented. Intuitively, clouds have both a positive and a negative effect on warming: Clouds exert a negative effect on temperature by reflecting sunlight off into space, and they have a positive effect by trapping heat from below. It is generally accepted that cloud feedback is an important determinant of observed differences in estimates of global warming [33]. Conjectures about the direction and magnitude of cloud feedback effects vary significantly; also, the factors that most influence cloud behavior (e.g., type, amount, height distribution, etc.) are poorly understood, and realistic models are several years away.

An important aspect of global climate change assessment concerns the manner in which the carbon cycle is modeled. The storage and transport of carbon in the atmosphere is a process that is only partially understood. During the course of the past decade, atmospheric scientists have improved their understanding of how the removal of CO_2 from the atmosphere is distributed between sinks in the ocean and on land. In this biological, chemical, and physical process, carbon is transferred or exchanged between the atmosphere, oceans, and terrestrial biosphere.

The role of the oceans in absorbing CO_2, as well as in storing and transporting heat, is also poorly understood. The Earth's oceans transport roughly 50% of the heat carried from the equator to the pole. In the global climate system, the net uptake of anthropogenic CO_2 by the deep oceans occurs very slowly. Consequently, anthropogenic CO_2 has a long-lasting effect on atmospheric concentrations and future climate. While it is true that the oceans also slow temperature change, fundamental uncertainty exists as to the rate at which heat is transported downward in

[13] For example, as Lindzen [28] points out, very little is known about the factors that determine the equator-to-pole temperature distribution. Knowledge about this distribution bears directly on our understanding of the processes that determine the mean surface temperature of the Earth.

the ocean. Later, we discuss the potential role that the oceans play in influencing tropical cyclone activity.

The task of modeling the global climate system is further complicated by other factors, as well. For example, the specification of the climate system's initial conditions is an inherently problematic task. Equally important, the global climate system is characterized by a complex array of interactions and feedbacks, knowledge of which is also highly uncertain. Complicating matters further is the fact that these climatic interactions and feedbacks occur at different levels of both spatial and temporal resolution.

Types of Climate Models

There are, of course, many ways to model the global climate system. In general, all numerical climate models must address the following set of issues [30]:

- **Radiation**. The input and absorption of incoming solar radiation; emission of outgoing infrared radiation.
- **Dynamics**. The movement of energy around the globe, from low to high latitudes, as well as vertical movements.
- **Surface Processes**. The role of land/ocean/ice interactions and the resultant change(s) in albedo, emissivity, and surface-atmosphere energy interchanges.
- **Resolution in Space and Time**. The time-step of the model, as well as the resolution of the horizontal and vertical scales.

The manner and degree to which these facets of the climate system are represented in numerical climate models depends, in large measure, upon the climate model type. In general, there are four basic types of climate models:

- **Energy Balance Models**. Zero- and one-dimensional models that are used to predict either globally averaged temperature or the variation of the Earth's surface temperature with latitude. Models of this type are useful for evaluating scenarios of future climate change, as well as for developing parameterizations that explore climate system sensitivities. Energy balance models (EBM) play a prominent role in so-called integrated assessments of global climate change, which seek to integrate the science and economics of climate change in ways that are useful to decision-makers. In Appendix A, we present two EBM-based representations of the global climate system that are often used in integrated assessments of climate change. [14]

[14] See, e.g., Valverde [45].

- **One-Dimensional Radiative-Convective Models**. Models that make explicit calculations of the fluxes of solar and terrestrial radiation. Models of this type usually include detailed representations of radiative transfer and atmospheric chemistry. Such models usually compute vertical globally averaged temperature profiles by modeling the radiative process with a "convective adjustment" that re-establishes a predetermined lapse rate. [15]

- **Two-Dimensional Statistical Dynamical Models**. Models that represent surface processes and dynamics in a zonally averaged manner, with a vertically resolved atmosphere.

- **General Circulation Models**. Models that utilize fundamental equations that describe flows of mass, momentum, and heat, to model the three-dimensional nature of the atmosphere and ocean; such models typically have a higher spatial resolution than other types of climate models.

Climate Sensitivity and Intermodel Comparisons

An important scientific uncertainty in the greenhouse debate concerns the expected change in global-mean surface temperature that results from increases in atmospheric concentrations of key GHGs. The models described above all play a role in present-day efforts to assess the influence of GHGs on climatic change. These gases include — in addition to CO_2 — methane (CH_4), nitrous oxide (N_2O), the CFCs, and, most importantly, water vapor. [16] Factors that determine the atmospheric concentrations of GHGs from known emissions are moderately well understood, though current forecasts of CFC concentrations are thought to be much more certain than forecasts of CO_2, CH_4, and N_2O.

A useful benchmark for comparing models is the *climate sensitivity* value, which is defined as the *equilibrium response* of the global climate system to a static doubling of atmospheric CO_2 concentrations. Most scientists believe that the range 1 – 5°C is likely to contain the true climate sensitivity value. [17] If there were no change in the concentration of water vapor, a static doubling of atmospheric CO_2 would give rise to a global mean surface temperature increase of approximately $\Delta T_{\mathrm{d}} \approx 1.2°\mathrm{C}$. [18] However, as water evaporates with increasing temperature, the concentration of water vapor in the Earth's atmosphere is expected to increase; this effect could,

[15] The *lapse rate* is the rate at which temperature decreases as a function of height in the atmosphere.

[16] The concentration of water vapor varies rapidly in space and time, and this variation arises from climate feedback mechanisms that are currently not well understood.

[17] See, e.g., National Academy of Sciences [34] and the Intergovernmental Panel on Climate Change [20]. Cf. Jacoby and Prinn [24, p. 13–16] for an insightful discussion of the various interpretations that can be attached to the Intergovernmental Panel's climate sensitivity range. The controversy and uncertainty surrounding this value is still very much alive. See, e.g., Harrabin [17].

[18] This estimate depends on the assumption that the cooling of the Earth is from the stratosphere, and that there is a fixed air temperature distribution with height.

in turn, amplify warming. In addition, water can introduce interactive feedbacks into the climate system, such as water vapor, clouds (especially cirrus clouds), and snow-ice albedo. Feedbacks such as these introduce considerable uncertainty into long-term predictions of global-mean surface temperature changes resulting from increases in atmospheric concentrations of key GHGs.

Global-mean surface temperature, $\Delta T_{\rm s}$, is roughly related to $\Delta T_{\rm d}$ by the formula

$$\Delta T_{\rm s} = \Delta T_{\rm d} \,/\, (1 - f),$$

where f denotes the sum of all climate feedbacks. The water vapor feedback is relatively simple, in that a warmer atmosphere is likely to contain more water vapor. This process gives rise to a positive feedback: An increase in one greenhouse gas, CO_2, induces an increase in another greenhouse gas, namely, water vapor. Cloud feedback, however, is harder to evaluate, because it depends on the difference between the warming caused by the reduced emission of infrared radiation from the Earth into outer space and the cooling through reduced absorption of solar radiation. The net effect is determined by the amount of clouds, their altitude, and their water content. Estimates for $\Delta T_{\rm s}$ from different models vary from 1.9°C to 5.2°C [10].

It is worth noting that two models which give similar values for $\Delta T_{\rm s}$ values can differ in the effects of various feedback mechanisms. For example, two GCM models — GFDL and GISS [19] — show an unequal temperature increase as clouds are included (from 1.7°C and 2.0°C to 2.0°C and 3.2°C, respectively). The effects of ice albedo in these two models are different, but opposite, so that the results converge (4.0°C versus 4.2°C, respectively). What this example shows is that *agreement between models may be spurious and potentially misleading*. In addition, many climate experts believe that f is high enough (~ 0.70) that *even small increases in this value could result in a runaway warming that is not predicted by current models* [29,41].

Key Uncertainties in Regional Climate Prediction

Focusing, as we have, on issues pertaining to scientific uncertainty, it is easy to lose sight of the one challenge that is absolutely central to most real-world decision contexts where climate is a key consideration, namely, *regional climate prediction*. The need for predictive capability of this kind permeates many of the most important practical dimensions of the greenhouse debate, including carbon emissions projection, catastrophe modeling, climate prediction, economic analysis of control policies, and the assessment of social and environmental impacts. Unfortunately,

[19] See, e.g., Hansen et al. [16].

this is one area in particular where the science of climate change is unlikely to yield much in the way of useful technology for many years to come.

One reason for this lack of predictive capability is that General Circulation Models — by far the most sophisticated tools for performing global climate simulations — are ill-suited for this task, in that the computational costs required to perform long-term simulations of regional climate are largely prohibitive. As a consequence, GCMs are typically "downscaled" — with concomitant increases in *spatial* or *temporal* resolution — in order to emphasize particular aspects of the climate system that lend themselves to regional predictions of climate change.

While progress has been made in the development of increasingly sophisticated downscaled models, the uncertainties inherent in these reduced models is vast. For instance, as with any global climate model, these models require that numerical values be assigned to model parameters before they can be used to generate medium- to long-term projections of future climate. Of course, even conditional upon having specified a particular model's functional form, modelers are almost always uncertain *a priori* about what numerical values to assign to its parameters.[20] Within these kinds of downscaled models, examples of important parameter uncertainties include the following:

- **Cloud Feedback**. The cloud feedback simulated by many downscaled GCMs depends on the parameterizations of cloud cover. Letting $n(\phi, z)$ denote cloud cover at latitude ϕ and height z, the parameterization of cloud cover takes the functional form

  $$n(\phi, z) = \max\left\{ 0,\ \frac{A\,[r(\phi, z) - r_c]}{(1 - r_c)} \right\},$$

  where

  $$\begin{aligned} r &= \text{Relative humidity at}(\phi, z); \\ r_c &= \text{Critical humidity threshold}; \\ A &= \text{Empirical constant}. \end{aligned}$$

  This parameterization is similar to the parameterization used in many GCMs. Given this prescription for cloud cover as a function of humidity, the change in $n(\phi, z)$ over location and time will determine cloud feedback behavior. Conditional on accepting this model structure, knowledge of either A or r_c would allow us to compute a reasonable value of the other from observed data. Unfortunately, the values of A or r_c that most adequately represent cloud cover are not well understood.

[20]The continuing controversy about the numerical value to assign to the feedback multiplier in the computation of equilibrium change in global-mean surface temperature is an example of a parameter uncertainty that gives rise to large spreads in expert judgements about climate sensitivity.

- **Rapidity of Deep Ocean Mixing**. Both heat and CO_2 mixing within the deep ocean are often represented as simple diffusion within downscaled climate models. The magnitude of the diffusion coefficient, which is a function $K(\phi)$ of latitude, is uncertain, but lies within a broad , finite range, $0 < K(\phi) < 10$ cm^2/sec. Heat flux $F(\phi, z)$ at a given ϕ and z is directly proportional to K in the diffusion equation
$$F(\phi, z) = -\rho\, C\, K(\phi)\, \frac{\partial T(\phi, z)}{\partial z},$$
where ρ is the water density, C is water heat capacity, and $\partial T(\phi, z)/\partial z$ is the temperature gradient in the vertical direction. If $K(\phi)$ is uncertain, it follows that heat flux $F(\phi, z)$ is also uncertain.

- **Initial Temperature of the Deep Ocean**. Current scientific knowledge does not allow us to know with certainty if the deep ocean temperature is, in actuality, an equilibrium temperature. If $T_0(\phi)$ is the deep ocean temperature for current climate and $T_e(\phi)$ is the corresponding deep ocean equilibrium temperature, then the future evolution of temperature depends on $T_0(\phi) - T_e(\phi) = \delta T(\phi)$. But, $\delta T(\phi)$ is not known with certainty.

Naturally, computational capacity places very stringent boundaries on our ability to perform systematic and exhaustive analyses of regional climate change. Even though many downscaled models are hundreds of times faster than their GCM counterparts (at, say, $4^\circ \times 5^\circ$ resolution), the computational costs involved in running these downscaled models are sufficiently high to make their integration into formal risk management frameworks a practical impossibility at the present time. [21] In what follows, we explore the challenges that scientists and modelers currently face in arriving at reliable estimates of future changes in regional climate in the context of ongoing efforts to explore the manner and degree to which anthropogenic climate change and extreme weather are conjoined.

[21] In order to deal effectively with these computational restrictions, catastrophe modelers and risk managers must focus their modeling efforts on the development of *reduced-scale* representations of the global climate system, an example of which is presented in Appendix A.

3. Climate Change and Extreme Weather

The preceding section explored several key facets of the scientific basis that underlies our current understanding of the causes and consequences of global climate change. As part of this discussion, we explored several types of models that climate scientists use to represent the components that comprise the global climate system, as well as the sources of uncertainty in these models. With this as background, we now take up the issue of the potential linkage between anthropogenic climate change and extreme weather, with particular emphasis on tropical cyclone activity in the North Atlantic. We frame our discussion in terms of ongoing efforts to arrive at reliable estimates of future tropical cyclone activity — both on a global and a regional basis.

Is there a Connection?

The destructive hurricane seasons of 2004 and 2005 in the United States have left many within the insurance and reinsurance industries openly questioning whether the observed increases in the number of tropical storms and hurricanes in the North Atlantic might, in some way, be linked to anthropogenically induced climate change. As we discussed earlier, the science of climate change offers little in the way of clear and definitive answers to many of the most pressing issues facing public and private stakeholders who share a mutual interest in, and concern for, issues pertaining to global environmental change.

For insurers and reinsurers, a key question is this: *Will the frequency or the intensity of future tropical cyclone activity be measurably enhanced in a GHG-warmed world?* In approaching this question, it is useful to distinguish between two types of risk: *event risk* and *outcome risk*. Assessments of event risk focus on characterizations of *frequency* or *likelihood* for particular hazards (e.g., hurricane activity in the North Atlantic); assessments of outcome risk focus on the *valuation of outcomes* associated with specific hazards or events (e.g., pre-event estimates of insured loss). The dichotomy between event risk and outcome risk serves as a useful conceptual vehicle for exploring the balance of scientific evidence that exists as to the potential linkage between anthropogenic climate change and extreme weather. In what follows, we look specifically at ongoing efforts to estimate future changes in hurricane frequency and intensity, together with changes in vulnerability and exposure.

Estimating Hurricane Frequency

Variability is an endemic feature of the Earth's climate. Understanding the natural climatic variability of the globe is therefore central to understanding the potential

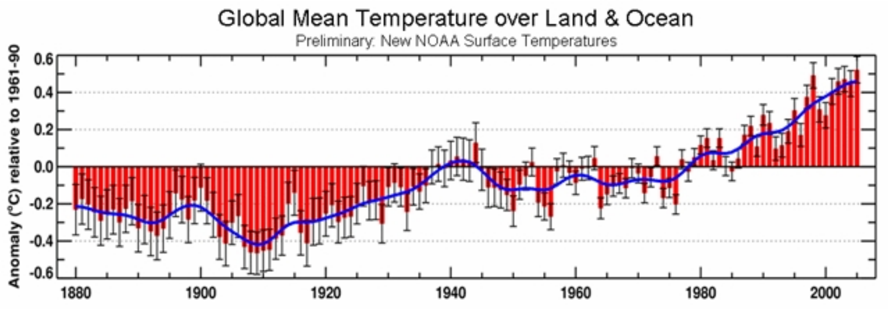

Fig. 3. Changes in global mean surface temperature relative to 1961–1990 (source: NOAA).

influence that anthropogenic factors might have on global climate change. Globally, the 1980s and 1990s were characterized by unusually warm weather. In fact, eight of the 10 warmest years in the past century occurred during this time period. As Figure 3 illustrates, an increase in global mean surface temperature change (of about 0.3°C – 0.6°C) has occurred since about 1860. A cursory glance at this figure reveals both *year-to-year* and *decade-to-decade variability* in the historical record; and even though there is a distinct warming trend, the increase is nonuniform, with periods of both *cooling* and *warming*.

Turning to the specific issue of hurricane activity in the North Atlantic, Figure 4 illustrates that the mid-1990s marked the beginning of a period of pronounced increases in the annual number of named storms and major hurricanes in this region. In the Atlantic hurricane season of 2005, for example, there were a record-breaking 27 named storms, 14 of which were hurricanes. Of these 14 hurricanes, seven were classified as major hurricanes; three of these seven major hurricanes reached Category 5 status.

The observed variability in hurricane frequency in the past decade is not so extreme that it cannot be explained in terms of naturally occurring multi-decadal variability. The global historical record for tropical cyclones yields several important insights in this regard. First, it is important to note that globally, there has been *no appreciable increase in tropical cyclone activity over the past several decades.* Webster et al. [47], for example, note that over the past 30 years, there has been *no trend towards either increases or decreases* in the total number of storms seen in a given year. Indeed, from a global perspective, these results are not surprising, as the past half-decade or so has seen heightened levels of hurricane activity, whereas the 1970s, 1980s, and early 1990s were marked by diminished levels of hurricane activity. One has to look as far back as the 1940s, 1950s, and the early 1960s to find hurricane activity levels commensurate with present levels.

Regional variability in the number of tropical storms and hurricanes complicates efforts to arrive at a comprehensive and global understanding of the key determinants of tropical cyclone frequency — be they man-made or naturally occurring. Indeed, while storms in the North Atlantic have become more frequent since the 1990s, in other parts of the world — such as the Western and Eastern Pacific — tropical

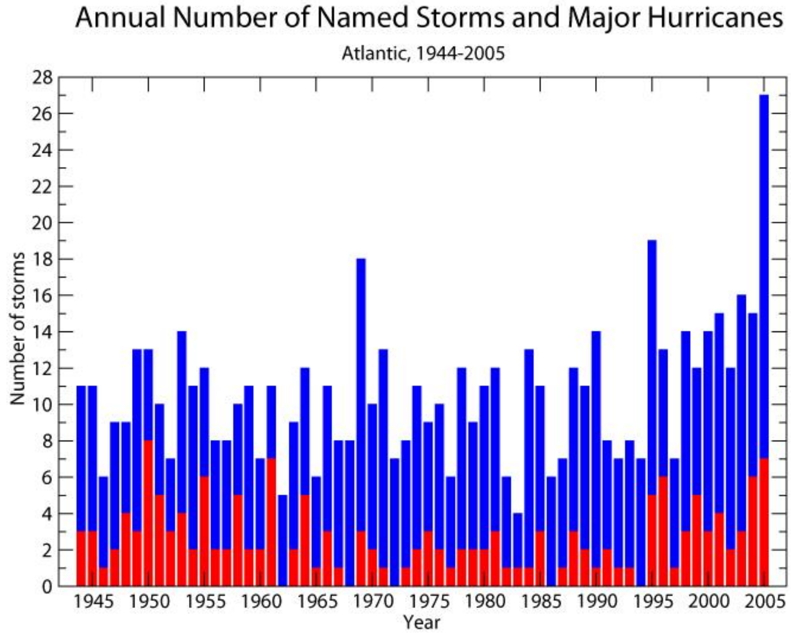

Fig. 4. Annual number of named storms and major hurricanes: Atlantic, 1944–2005; named storms are depicted in blue and major hurricanes are depicted in red (source: NOAA).

cyclone frequency has, in fact, *declined* since the early 1990s. As Webster et al. describe, the current situation is one where "against a background of increasing sea surface temperature, no *global trend* has emerged in the *number* of tropical storms and hurricanes" [emphasis added]. As we discuss below, our current inability to arrive at global insights has important ramifications for ongoing efforts to arrive at *regional* characterizations of the behavioral dynamics of tropical cyclones.

In all of this, we are, of course, keenly interested in deriving reliable estimates of the frequency of *future* tropical cyclone activity. As described above, however, current efforts to utilize the available historical record to discern trends — which can, in turn, be used as the basis for deriving forward-looking projections of future tropical cyclone activity — have led to largely inconclusive results.

Given these limitations, climate scientists also pursue a number of global modeling efforts that seek to arrive at realistic representations of the global climate system; these representations are then used to produce model-derived projections of future tropical cyclone activity. While progress has been made in developing increasingly sophisticated models of the global climate system, the climate change research that bears most directly on questions concerning potential future changes in hurricane frequency arising from greenhouse warming is, at best, ambiguous. The major modeling results published in recent years lack consistency in projecting *increases* or *decreases* in the total number of storms. [22]

One area where the empirical studies and the global modeling results are in agreement is in projecting that future changes in tropical cyclone frequency will be *regionally dependent*. If true, this situation will require modeling efforts that are capable of rendering informative regional forecasts and scenarios. At the present time, though, climate scientists' understanding of *tropical cyclogenisis* is too incomplete to render reliable projections about future changes in tropical cyclone frequency. This observation notwithstanding, what the historical record illustrates with great clarity is that future changes in hurricane frequency are likely to exhibit considerable year-to-year and decade-to-decade variability.

Estimating Hurricane Intensity

The analytical task of discerning trends in tropical cyclone intensity is more complex than that of estimating tropical cyclone frequency. One reason for this is that there are, in fact, several plausible measures of storm intensity. Table 1 lists several measures in common usage. As before, it is useful to begin our discussion by examining the historical record for indications of how tropical cyclone intensity has varied over time. The empirical record reveals that, over the past half-century, tropical and subtropical sea-surface temperatures have shown an overall increase of approximately 0.2°C. Although most global modeling studies predict increases in modeled storm intensities under greenhouse warming scenarios, the statistical evidence in favor of hypotheses that postulate *systematic* increases in potential storm intensities is weak. [23] Webster et al., for example, note that globally, since 1970, the annual number of Category 1 hurricanes has declined, whereas the number of Category 2 and Category 3 hurricanes has fluctuated (though the global average has, nevertheless, remained fairly constant over the same time horizon). Over the same time period, the number of Category 4 and Category 5 hurricanes has increased.

At present, there is only weak evidence suggesting the possibility of a systematic increase in the potential intensity of future tropical cyclone activity. Emanuel [13], for example, reports a discernable upward trend in power dissipation [24] in the North Atlantic and the Western North Pacific. And while the observed trend is dramatic (a factor of two increase over the past half century), *the underlying causal mechanisms are far from being well-understood*.

In the North Atlantic — consistent with our earlier remarks about storm frequency — recent increasing trends in Atlantic storm intensity can largely be explained

[22] See, e.g., Henderson-Sellars et al. [19], Royer et al. [37], and Sugi et al. [42].

[23] See, e.g., Free et al. [15].

[24] Power dissipation measures the total amount of energy released by a hurricane over its lifetime. Technically, Emanuel [13] defines the annual *power dissipation index* (PDI) as the integral of the third power of the maximum sustained wind speed over all 6-hour observations at tropical storm intensity or higher and over all tropical cyclones during the year.

Measures of Intensity
• Maximum Potential Intensity
• Average Intensity
• Average Storm Lifetime
• Average Wind Speed
• Maximum Sustained Wind Speed
• Maximum Wind Gust
• Accumulated Cyclone Energy
• Minimum Central Pressure
• Power Dissipation

Table 1
Common measures of tropical cyclone intensity.

by multi-decadal variations that are, in some respects, better understood than the physical theories that attempt to relate storm intensity to tropical climate change. Numerous statistical studies have mined the available empirical record for evidence of anthropogenically-induced trends; still, no significant anthropogenic trends have emerged from these studies. [25]

Having explored the relevant empirical findings, let us return to the global modeling studies that we discussed earlier, this time exploring the model-based, theoretical insights that have emerged in recent years about the influence that anthropogenically-induced greenhouse warming might have on hurricane activity in the United States.

Early efforts along these lines gave many interested stakeholders pause for concern. In 1987, for example, Emanuel [12] reported that a doubling of atmospheric CO_2 levels would give rise to increased sea-surface temperatures, eventually producing 40–50% increases in the maximum strength of hurricanes. [26] The very latest global modeling studies have sought to explore the manner and degree to which anthropogenically-induced warming influences tropical cyclone intensity. Some studies suggest that the projected changes in tropical cyclone intensity are small. Emanuel, for example, reports a 10% increase in wind speed for a 2°C increase in tropical sea surface temperature. [27]

In interpreting these results for insurance-related risk management contexts, it is important to recognize that an endemic feature of the types of global simulation

[25] See, e.g., Landsea et al. [27] and Chan and Liu [9].

[26] As alarming as these predictions were, it is worth noting that, at around this same time, equally credible scientists were arguing the reverse, i.e., that greenhouse warming could, in fact, give rise to *decreases* in hurricane frequency and intensity. See, e.g., Idso [23] and Idso et al. [22].

[27] Two sets of published results suggest that Emanuel's estimates may, in fact, overstate the true value of these projected increases. Researchers using the GFDL model, for example, report a 5% increase in hurricane wind speeds by 2080 [1,26]; more recently, Michaels et al. [31] report even smaller increases over comparable time horizons.

studies discussed above is that they lend little insight into questions concerning the *timing* of these projected increases. In many of these global modeling studies, modeled changes in tropical cyclone intensity unfold over very extended time horizons. As Knutson and Tuleya [26] note, "CO_2-induced tropical cyclone intensity changes are *unlikely to be detectable* in historical observations and will *probably not be detectable for decades to come*" [emphasis added]. Michaels et al. [31] echo this belief — and take it, perhaps, one step further — with their assertion that changes in "future hurricane intensities will be *undetectable in the foreseeable future* and, in fact, *may never be manifest*" [emphasis added].

As before, arriving at reliable assessments of regional climate change is, perhaps, the greatest challenge facing climate modelers today. The ability to link — conceptually and empirically — anthropogenic climate change to storm intensity in ways that lend themselves to modeling efforts that yield reliable regional forecasts is, unfortunately, some years away.

Estimating Hurricane Risk Exposure

From a risk management perspective, our discussion above concerning the frequency and intensity of future tropical cyclone activity is, of course, just one-half of the overall problem. The other half of the problem concerns the *vulnerability* and *exposure* dimensions of hurricane risk. Arriving at reliable estimates of economic and insured loss requires an understanding of how vulnerable specific geographic regions or structures are to extreme weather events. In seeking quantified estimates of vulnerability to extreme weather, modelers begin by characterizing the inventory of persons and properties at risk. Knowledge about inventory and vulnerability — combined with knowledge and information about the natural hazard itself — allows risk managers to quantify the expected impacts and outcomes associated with extreme weather events.

Most efforts to characterize the primary drivers of hurricane risk exposure focus on two factors:

- How society develops in terms of changing demographics;

- How society prepares itself for storms.

From a risk-based perspective, the vulnerability and exposure dimensions of the problem will almost surely dominate any influence that variations in storm frequency and intensity — be they caused by natural or man-made factors — will have on overall characterizations of risk for particular geographic regions of the country. Indeed, the major source of worry concerning hurricane risk exposure in the United States is the fact that the size of coastal populations will grow faster than

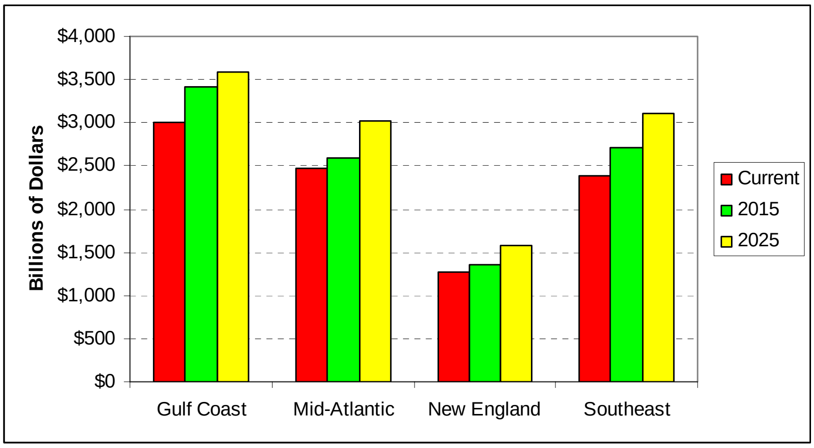

Fig. 5. Value of coastal property, 2005–2025: 1/2% growth (source: U.S. Census Bureau; I.I.I.).

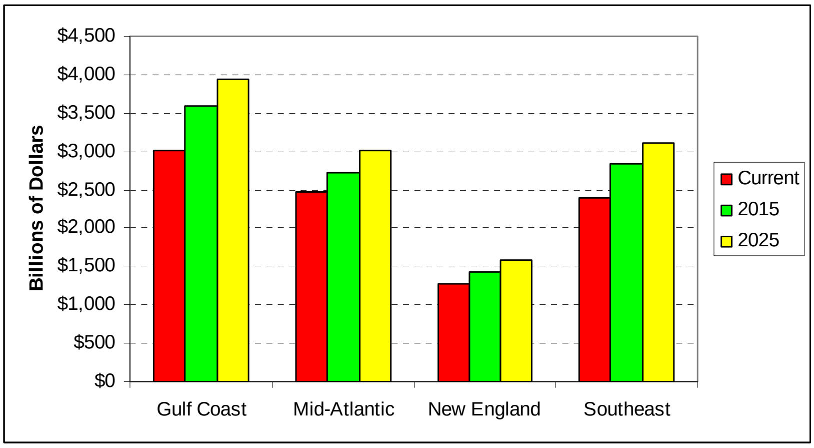

Fig. 6. Value of coastal property, 2005–2025: 1% growth (source: U.S. Census Bureau; I.I.I.).

the overall population, thereby boosting the number of persons and the amount and value of property in the path of potentially destructive hurricanes.

The best available projections of the country's rapidly changing demographics paint a potentially dire situation. These projections, when combined with conservative assumptions about the growth of property ownership per person in coastal areas, suggests that we will continue to see substantial increases in the value of coastal properties vulnerable to hurricanes. Figures 5 and 6 show the value of vulnerable coastal properties that will exist in 2015 and 2025 assuming (i) A one-half of one percent annual increase in the inflation adjusted value of coastal property per person; and (ii) A one percent annual increase in coastal property holdings per person. [28] The rapid growth of the Gulf States will lead to an explosion in the value of vulnerable property, despite the modest per person property growth rates assumed, compared to the exposure of slower growing regions (such as the Mid-Atlantic and New England) or the Southeast.

Looking forward, the risk management challenges that arise from these problems are two-fold in nature. First, research efforts must continue to strive to develop meaningful *regional* forecasts of tropical cyclone activity. How uncertainty is characterized and evaluated in these forecasts is an issue very much at the forefront of current research. Researchers and catastrophe modelers will, of course, continue to mine the available historical record for emerging patterns and trends, and, over time, these efforts will lend themselves to predictive exercises that yield insights that are useful to decision-makers. Second, in the absence of regional forecasts that engender confidence on the part of decision-makers and risk managers, efforts must focus on arriving at strategic risk mitigation options that are — to some measurable degree — flexible, robust, and resilient.

[28] Note that Florida is included in both the Southeast and Gulf Coast tallies.

4. The P/C Industry and Extreme Weather

Practical people in the insurance industry may be forgiven their impatience with a paper on climate change and scientific uncertainty which suggests that we do not, as yet, know enough about the connection between climate change and extreme weather to make operable forecasts of what lies ahead. [29] We can, however, use past information about the connection between insurance industry profitability and extreme weather events to get a rough idea of the impact that climatic change might have on the bottom line of insurers, under a wide range of possible worlds.

A Direct Approach to the Bottom Line

One way to proceed is to ask a seemingly simple question: How have extreme weather events — in this case, hurricanes characterized by very large insured losses — affected the *return on equity* earned by insurers in any given year? Figure 7 presents the return on equity for U.S. P/C insurers and reinsurers between 1950 and 2005, with select annotations for years with exceptionally large losses. The first thing to notice is that large hurricane losses have been experienced in years with excellent as well as poor industry performance. Indeed, it seems strange to think that large hurricane losses might not regularly lead to low returns for insurers, though a moment's reflection suggests that well-run insurers will structure their portfolio of risks so that large losses in some lines of business are offset by strong performance in others, combined with reinsurance and skilled financial management of overall policyholders' surplus. A perpetual concern of insurers and underwriters, though, is how sustainable sound financial performance can be in the face of multiple high-loss hurricanes, perhaps over the course of successive years.

In this regard, we begin with two notes of caution. First, the following analysis seeks an answer to a very specific question: What is the impact of very large loss hurricanes on the return on equity for the US insurance industry as a whole? The answer to this question may seem obvious, since large loss hurricanes must, by definition, push aggregate industry returns down. Our question, though, is a bit subtler: Is there a systematic, quantitative relationship between the number and size of extreme loss hurricanes and insurance industry return on equity that permits observers to make informed guesses about the potential impact of climatic change on the performance of the insurance industry?

[29] A complete analysis of the economic consequences of scientific uncertainty in broader study would include a review of the economic theory of climate change, including: a detailed assessment of analytical work on global public goods; the game theoretic aspects of climate policy in a world of nation states; the public finance and macroeconomic aspects of pricing climatic changed based externalities, as well as investments by national and international governmental and non-governmental entities in mitigation. Readers seeking a fuller understanding of the economics of climate change are urgued to consult the recent books by economic theorist Hirofumi Uzawa, whose recent works – see, e.g., Uzawa [44] – explore the interaction of climate change, markets, and policy.

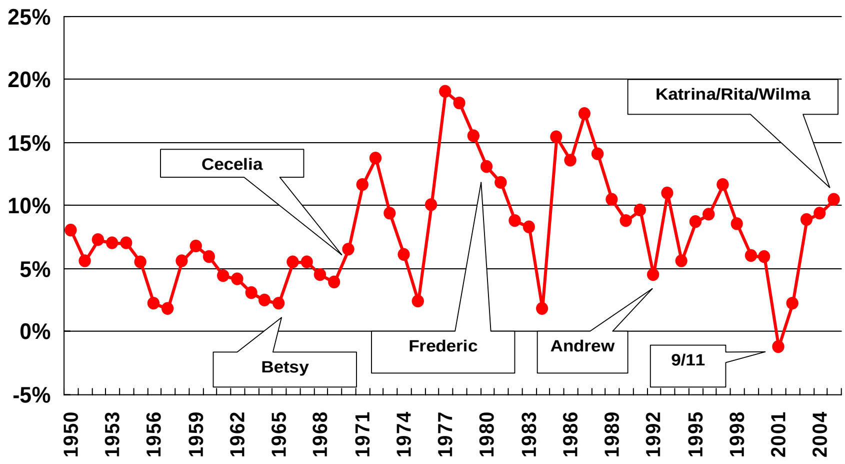

Fig. 7. Impact of selected large loss hurricanes on return on equity for the insurance industry: 1950 – 2005 (GAAP ROEs, with the exception of the 2005 P/C figure, which is the return on average surplus; the 2005 figure is the I.I.I. full-year estimate; source: I.I.I..

Second, our aggregate approach has certain inherent limitations that must be kept in mind when considering our results. The "industry" return on equity is, like all summary measures, an amalgamation that obscures many important details that matter for our assessment of how large-loss hurricanes affect insurers. Many insurers face little exposure to hurricane risk, so any connection between hurricanes and *aggregate* industry performance is necessarily weaker than that between extreme storms and, say, homeowners' lines. The coastal concentration of hurricane losses, along with the various regulatory systems affecting the operations of insurers in the relevant states, are important details that the aggregate approach pursued in this paper does not take into account. In addition, a substantial portion of losses associated with large hurricanes striking the US mainland are actually borne by foreign domiciled re-insurers, thereby limiting the extent to which extreme hurricane losses impinge on the immediate financial condition of US insurers in the year of their occurrence. However, the transfer of hurricane losses to offshore reinsurers has a powerful effect on the price, availability, and other terms of future reinsurance dealings between U.S. primary insurers and reinsurers. The resulting dynamics of the prices, quantities, and limits that emerge in the reinsurance markets are the subject of future study.

With these two note of caution in mind, we begin by looking first at the frequency of large hurricane losses, especially compared to total policyholders' surplus. Figure 8 shows that hurricane losses relative to insurance industry policyholders' surplus between 1950 and 2005 have been relatively small, with more than 30 years where this loss ratio was less than one tenth of one percent. In fact, there have only been 7 years where hurricane loss ratios were 2% or more of policyholders' surplus. [30]

[30] Hurricane loss data comes from three sources: (1) The Insurance Information Institute's Insurance Fact Book 2006; (2) The publication *A Half Century of Hurricane Experience* by the Insurance Services Office in 2000; and (3) The National Oceanic

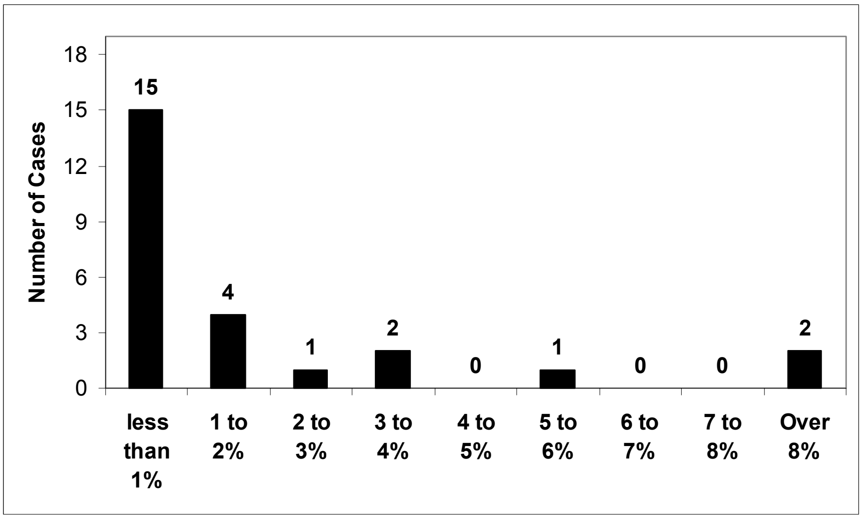

Fig. 8. The distribution of the ratio of hurricane losses to policyholder surplus: 1950 – 2005 (source: I.I.I.).

However, as Figure 8 illustrates, the bulk of large losses have occurred in recent years, beginning with Hurricane Hugo in 1989, through to the 2004 Quartet and the Katrina/Rita/Wilma Trio in 2005.

Figure 9 shows the evolution of the ratio of hurricane losses to policyholder surplus from 1950 – 2005. This figure may be a bit alarming to a casual empiricist, as it vaguely suggests a hurricane loss ratio cycle of increasing amplitude, which would be consistent with heightened fears about increasing hurricane activity. These escalating peaks can, however, be explained by many factors, including the spectacular long-term economic boom and population growth in the southeastern United States over the past forty years (with much acceleration since the mid-1980s) that has placed more people and property in harm's way, thereby increasing the likelihood of greater storm losses.

Collectively, Figures 7 – 9 offer a muddled picture of the relationship between hurricane losses and insurer profits. On the one hand, Figure 7 suggests no consistent link between hurricanes and P/C industry profits. Figure 8 suggests that hurricanes big enough to significantly damage policyholders'surplus are infrequent. Finally, Figure 9 opens the door — however slightly — to the prospect of increasingly severe losses, though these losses cannot definitely be linked to climate change.

Econometric analysis can lend some clarity to this muddled situation. It is worth noting from the outset that the analysis set forth here (the details of which are presented in Appendix B) fails to detect any consistent connection between large hurricanes and the return on equity of the insurance industry as a whole. In fact,

and Atmospheric Administration's "Billion Dollar Weather Disasters" web portal.

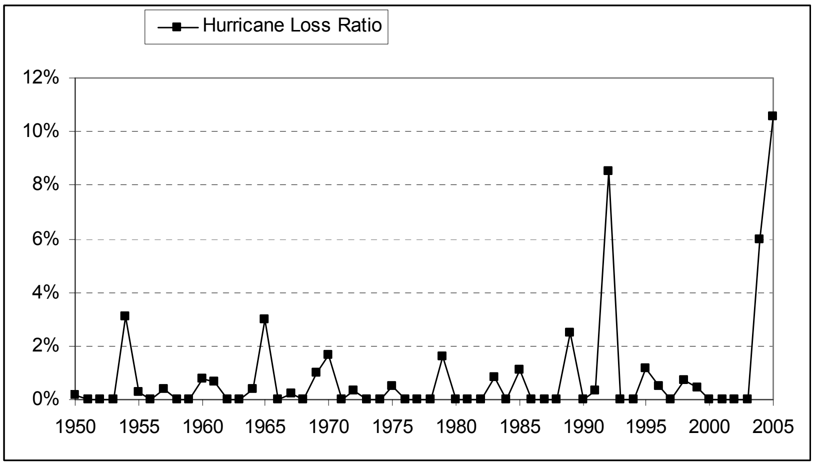

Fig. 9. Evolution of hurricane loss/policyholder surplus ratio: 1950 – 2005 (source: ISO; I.I.I.).

out results suggest that hurricanes are one of several essentially unpredictable risks that insurers must consider when covering personal and commercial lines. One explanation for this somewhat counterintuitive result, at least in the U.S., is that U.S. private insurers do not cover flood losses, so that a substantial part of the financial wreckage associated with large storms is not covered by private sector insurance markets.

This result does not mean that large hurricane losses do not affect insurers' aggregate returns, nor does it mean that large hurricane losses are in some way unimportant (as if "statistical insignificance" was somehow a synonym for "unimportant"). *The meaning of this statistical exercise is simply that large hurricane losses have no predictable impact on the recorded profits and, in turn, on the measured financial performance of the US insurance industry as a whole.*

Our point is subtle but can perhaps be clarified through an analogy to baseball: a given batter may have a higher batting average against left handed pitches than right handed pitchers but one may still not be able to predict that he will have more hits against lefties than righties in any given year going forward, or from now until the end of his career. It all depends on whether this difference is statistically significant. If so, we can be sure that our batter's past success against lefties will be reproduced in the future only if we can observe enough at bats for his tendencies to become predictable; if not, we can't say whether he will or will not be more successful against lefties in the future — maybe yes, maybe no. The lack of statistical significance does not prove the he isn't more successful against lefties, we just do not have enough evidence to make consistent predictions about how well he will do in the future. To say that the size or number of known hurricanes does not impose a statistically significant and therefore predictable penalty on the financial performance of the insurance industry is like saying that we do not have enough evidence to say that a hitter will always be more successful against left handed pitchers in the future even though he has been successful in the past. Once again, statistical significance is a statement about the quality and power of evidence required to make definitive statements in the midst of uncertainty, even if we know that a batter has so far feasted on left handed pitching, or that hurricanes have been a burden on insurers' profits.

The curious reader might be tempted to ask whether we can use the average decline in insurers' return on equity due to large hurricanes (1.94%) as a measure of the burden of hurricanes on the insurance industry, or rely on the mean and variance of large hurricane losses relative to policyholders' surplus to make educated guesses about the probability of extreme financial distress associated with extreme hurricanes. Such a procedure implicitly assumes that (i) we possess a good deal of knowledge about the probability distribution of hurricane losses relative to policyholders' surplus; and (ii) that the parameters of this distribution — whatever they may be — are either stable or evolving in predictable ways, which amounts to assuming away the problem of scientific uncertainty posed by climate change. Neither assumption is correct.

The point of this econometric exercise is to determine whether and to what extent hurricanes impose a predictable financial penalty on insurers so that we could then proceed with statistically informed speculation about how any increase in the frequency or severity of storms might affect the profits of insurers. Unfortunately, the results of our econometric exercise have not provided evidence that hurricanes reduce insurers' ROE in a consistent fashion, thereby making if quite difficult to assess the price that climate change extracts in terms of insurer profits in the event of more and more destructive storms.

One important implication of our analysis is that the lack of any statistically significant link between hurricanes and the rate of return to equity for insurers actually allows for informed guesses about the effects of a string of high-loss hurricanes on overall P/C industry losses over time. A conjecture of this sort is possible for two reasons. First, since hurricanes are not systematically linked to the rate of return on equity, a big loss in any one year might or might not pull down industry performance relative to trend, depending on the aggregate results of activity in other lines of business, risk management efforts and strategies, and financial market outcomes. A big, single storm associated with large losses can only have a substantial effect on the industry if other aspects of the business are weak as well. Of course, a tremendously destructive storm — the $100 billion mega-event that many within the industry fear — could be so far outside the range of losses experienced that it could strain many companies at once, thereby leading to potentially catastrophic results for the industry as a whole. This possibility is, however, partly offset by a second factor, namely, that the definition of a "large" hurricane loss is relative to the level of total industry policyholders' surplus at any point in time. A $100 billion loss would surely be a terrible blow to the industry in 2006, as total surplus is estimated to be $427B as of the end of 2005.[31] In any one year, a "large" hurricane loss is one that is substantial relative to the size of total industry surplus. Table 2 shows the current dollar value of the 10 largest hurricane losses, together with the level of industry surplus in the year that losses were incurred and the ratio of these losses to surplus.

Table Two

Hurricane	Year	Losses *	Total Surplus*	Ratio
Katrina	2005	$38.10	$427.20[1]	8.91%
Andrew	1992	$20.88	$200.54	10.41%
Charley	2004	$7.47	$402.26	1.85%
Ivan	2004	$7.11	$402.26	1.76%
Hugo	1989	$6.39	$166.44	3.83%
Wilma	2005	$6.10	$427.20	1.42%
Rita	2005	$4.70	$427.20	1.10%
Frances	2004	$4.59	$402.26	1.14%
Jeanne	2004	$3.65	$402.26	0.91%
Georges	1998	$3.36	$423.40	0.83%
WTC	2001	$18.80	$374.36	5.02%

* in billions of current dollars

Table 2
Top ten insured losses in current dollars and as a fraction of policyholders surplus (source: ISO; I.I.I.).

Our analysis reveals strong statistical connections between the return on equity earned by insurers and (i) the return on equity in the previous year; (ii) the return on 10-year U.S. government bonds in that year; and (iii) the growth rate of net premiums written over the year. Hurricanes are, by contrast, reduced to the status of *random forces* that drive the system in an unsystematic fashion. Figures 10 and 11 illustrate the movement of the 10-year Treasury bond rate and net premiums written relative to insurers profitability. We note that no matter what sort of hurricane measures were included in the model — e.g., the number of hurricanes in a year, the average strength of storms (as measured by the Saffir/Sampson scale) over a season, the effect of storms at varying levels of intensity, etc. — hurricanes were not seen to have a statistically significant impact on insurers' return on equity.

An important additional influence in the preferred equation is the impact of the destruction of the World Trade Center on the P/C rate of return in 2001. Indeed, the 9/11 atrocities had an outsized statistical impact on insurers' rate of return — a fall of more than 8 percentage points — that was greater than the direct 5.02% fall in surplus associated with the event. This apparent discrepancy can be reconciled

[31] This assumes that the random shocks affecting insurance returns include both hurricane and non-hurricane losses that are independent of each other, as well as unrelated to past values of P/C insurer returns, the 10-year Treasury bond rate, and WTC losses. This assumption implies that negative effect hurricane losses are generated by the same normal process that generates other, non-hurricane losses. However, if hurricane losses are generated by a non-normal process — one with a negative mean and homoskedastic variance – then the error term for the regression equation is the sum of a normal and non-normal shock. This implies that all tests of the statistical significance of coefficients, and inferences therefrom, must be based on a mixed compound distribution.

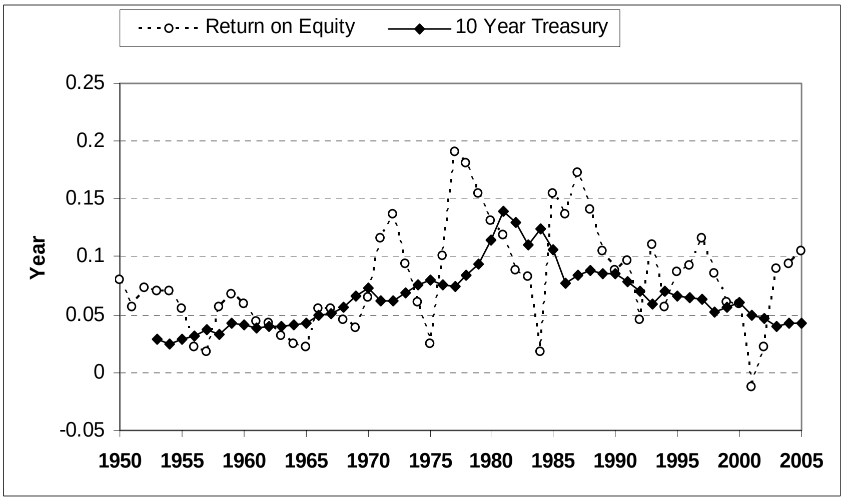

Fig. 10. P/C return on equity and the 10-year Treasury bond rate (GAAP ROEs, with the exception of the 2004/5 P/C figure, which is the return on average surplus; the 2005 figure is the I.I.I. full-year estimate; source: I.I.I.; *Economic Report of the President*).

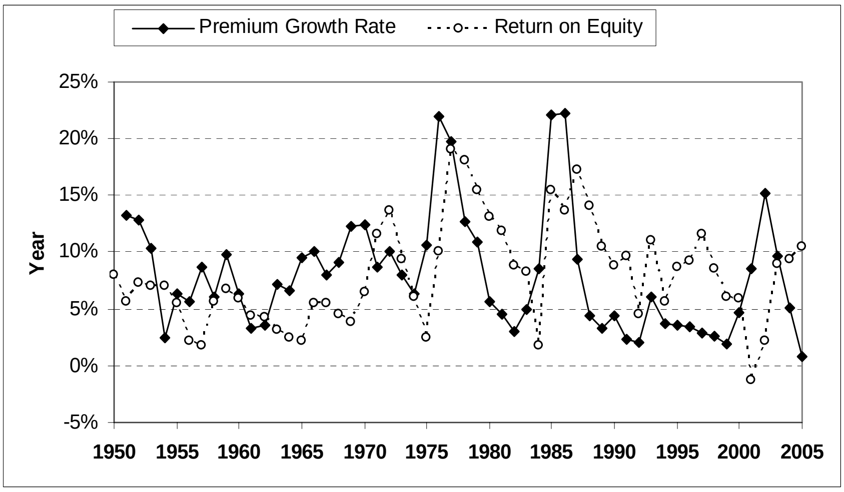

Fig. 11. P/C return on equity and yearly premium growth rates (GAAP ROEs, with the exception of the 2004/5 P/C figure, which is the return on average surplus; the 2005 figure is the I.I.I. full-year estimate; source: I.I.I.; *AM Best*).

when we recall that the economic impacts of 9/11 were so great that losses in many lines of business — not least airlines, ports, and other modes of transportation — were triggered when the Twin Towers fell. In addition, the statistical significance of events in 2001 for insurers' return on equity may be a mixture of the attacks on 9/11 and the downward pull of the Enron debacle, as well as related accounting scandals on the financial returns to policyholders' surplus.

The most important features of our analysis are the following:

- Hurricanes — even those associated with large losses — have no statistically detectable effect on the P/C industry's return on equity;

- The losses associated with the destruction of the World Trade Center — 5.02% of total policyholder surplus, as noted in Table 2 — are, according to the model, estimated to have cut the insurance industry's return on equity by about 8.1%;

- The WTC losses (relative to total policyholder surplus) are much less than those associated with Hurricane Katrina in 2005 (8.33%) and Hurricane Andrew in 1995 (10.41%), but are on par with those associated with the Hurricane Quartet in 2004 (5.66%).

These observations suggest two possible ways to think about the impacts of large loss hurricanes (either singly or in combination in a given year): (i) As random shocks to the industry that generate a longer-term response because of the dynamic links between past and present rates of return on equity demonstrated by this statistical exercise; or (ii) As monster hurricanes akin in size and scope to another WTC event that has a very pronounced negative effect on industry profitability, followed by reverberations into the future. Unfortunately, this second approach is based more on faith than evidence, since, once again, hurricanes do not have a consistent and statistically detectable effect on insurance industry returns.

Stormy Weather Ahead?

The current statistical exercise assumes that scientific uncertainty about global climate change permits insurers to look to the past to make informed guesses about how future increases in hurricane frequency and severity might affect overall industry profitability. If hurricanes are random negative influences on industry returns, as our model suggests, then it is nearly impossible to make reasonable guesses as to the long-term impact of a rise in the frequency and severity of hurricanes on profitability. However, we can construct another version of our model to arrive at a very rough estimate of the separate effects of "ordinary" random events (including small-loss hurricanes) and large-loss hurricanes on industry returns. [32]

Our analysis suggests that hurricane losses are random, negative shocks to insurers' returns that push profitability down immediately, with swiftly declining effects on future earnings (the reasons for these smallish feedback effects are explained in the appendix). Figure 12 presents four possible time-paths suggested by the estimated model in four possible hurricane loss scenarios:

[32] This macro-level analysis should be augmented by a detailed time series analysis of the connections between hurricanes, premiums and the profitability of specific lines — especially in homeowners' insurance — in specific states. This sort of analysis would require theoretical and empirical modeling of markets under various regulatory constraints which introduce complications in the dynamic and statistical properties of models that are well beyond the scope of the current exercise.

(1) No Quartet-scale hurricane losses between 2006 and 2018;

(2) One Quartet-scale storm;

(3) Two Quartet-scale storms;

(4) Three Quartet-scale storms.

These scenarios all assume that (i) the 10-year Treasury bond rate holds steady at 4.5% between 2006 and 2018; (ii) the rate of growth of net premiums is 8%; and (iii) there is no other major catastrophic event during this period — like another terrorist attack on the scale of 9/11. The scenarios consider Quartet-scale losses rather than Katrina-scale losses in the hope that the Great Flooding of New Orleans in 2005 was a unique disaster, unlikely to be repeated. This implies that the nation has learned to invest more of our tax dollars in protective capital so as to prevent a repeat of the suffering that followed Katrina's landfall in some other hapless venue. One extreme nightmare situation — a Katrina-scale loss followed by a 9/11-scale loss — is considered below, but only for the purposes of testing the consequences of a particularly extreme form of bad luck.

It is important to remember that the current exercise does not assume away terrorism, but rather, distinguishes between the seperate and distinct impacts of terrorism and large hurricanes on insurer profits. Recall that one result of our analysis is that the 9/11 attacks, combined with the downdraft of the accounting scandals of 2001, had a profoundly negative, if temporary, effect on insurers' return on equity that exceeded that associated with Katrina — in large part because the atrocities of that day generated further insured losses in other sectors of the economy due to the airline industry shutdown, business interruption in various locations, etc. Our strategy at this stage is to consider the impact of hurricane-scale losses on their own, and then to interrogate our analysis to determine the effect of a truly terrifying scenario where a series of Quartet-scale storms is accompanied by another 9/11-scale terrorist event.

Figure 12 is known as an impulse-response diagram — a workhorse in analytical economics, finance, and engineering — which illustrates the effect of an important economic shock on the evolution of variables of interest. The point of the diagram is to asses the impact of an important change — in this case, a series of Quartet-scale losses — on the return on equity over time, relative to what would have transpired had the shock not occurred. The dashed line in the diagram is the long-run return of equity for insurers' that would obtain for the indefinite future if the interest rate, premium growth, and terrorism loss assumptions noted above obtain. Each hurricane shock is represented by a different line in the diagram, permitting an evaluation of what the statistical model suggests will happen under each case.

This chart suggests a number of potential insights into the effects of a series of major storms on insurers' profitability. The long-run return or "no-Quartet" path is the

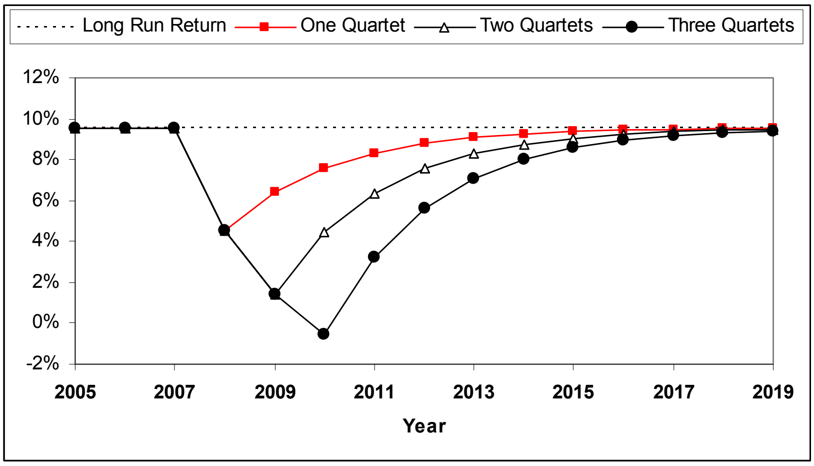

Fig. 12. Response of return on equity to one or more Quartet-scale storm losses.

reference path used to judge the impact of multiple Quartet-scale storms on insurer profits. A single Quartet-scale storm four years from the beginning of the simulation reduces insurers' return on equity by 5% in 2007, as shown by the sudden drop of the path indicated by squares. However, insurer return on equity recovers quite quickly thereafter — assuming no change in either premium growth or the 10-year Treasury bond rates — so that insurer returns associated with the one-Quartet path are close to the reference path by the year 2011, with no change in any other component of profitability. If the U.S. is struck by two Quartet-scale storms in 2007 and 2008, then return on equity is about 8.5% lower than the no-Quartet path by the end of year 2008, while three Quartets in years 2007 through 2009 results in returns that are slightly over 10% lower than in a world without major storm losses. Of course, a two or three storm sequence will push down industry returns for an extended period of time, though both the two- and three-Quartet paths display remarkable resilience.

The results depicted in Figure 12 contain a hopeful message for insurers who understandably dread the nightmare of a sequence of Quartet-scale storms over a number of years. The resilience of industry returns in the event of even a sequence of monster storms and the associated losses suggests that insurers' underwriting, pricing, and financial management policies will, in all likelihood, be adjusted to address threats to profitability posed by the possibility of increased hurricane frequency and severity. Note that the statistical analysis which grounds this simulation necessarily assumes that insurers' continue to operate as they have in the past, even in the face of a sequence of large storms, with the consequence that the time-path of returns in the worse-case scenario converges to within 20% of the reference path four years after the last great storm. The negative effect of a series of high-loss hurricanes can also be offset by high interest rates, improved underwriting margins, or by other mechanisms for offsetting very large losses.

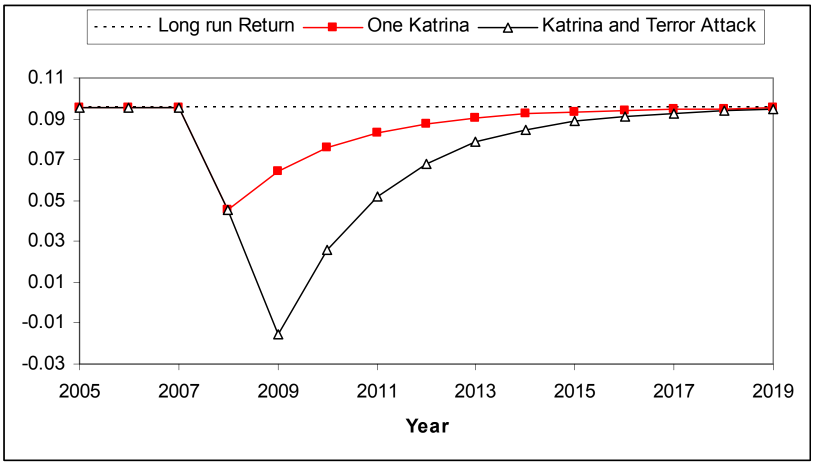

Fig. 13. Response of return on equity to nightmare compound scenarios.

A Short Glimpse at a Compound Nightmare

We now briefly consider a truly miserable scenario: a Katrina-scale hurricane loss in 2007 followed by a 9/11 terrorist loss in 2008. Figure 13 illustrates the projected time-path for return on equity in the unlikely and unfortunate event that a massive storm loss is subsequently followed by an even larger terrorism loss. The figure shows that insurers' profitability would be badly damaged by such a sequence of events, but would, again, recover to within 75% of the "no-storms / no-9/11" path by 2012.[33]

Insurance Industry Profitability in Context

In placing these analytical results in context, we must remember that the resilience of the industry's profitability in the face of a series of Quartet-scale storms is connected to the usual mechanisms of retrenchment by insurers in the face of large losses: higher premiums, higher deductibles, lower limits, and reduced insurance availability in high-risk areas. The robust adjustment process of profitability to large shocks displayed above, though comforting and indicative of the considerable power of market mechanisms, still leads to the withdrawal of capital from regions and lines of business hit by large, concentrated losses in favor of more lucrative lines within insurance and the broader financial services sector. A more finely grained econometric analysis — based, perhaps, on a dynamic, stochastic general equilibrium model of pricing, availability and risk portfolio choice by the industry — would reveal the statistical anatomy of industry adaptation observed in practice and consistent with economic common sense: restoration of insurers' prof-

[33]This analysis is conducted under the assumption that TRIEA is no longer in effect.

itability in the wake of a run of bad hurricanes includes the reallocation of capital to more remunerative and safer activities.

The withdrawal of capital from high-risk areas hit by big storms will naturally lead to more expensive insurance in states where regulators allow market pricing to operate, or to an even more severe reduction in availability where government prevents the price mechanism from working. In this matter, as in many others areas of insurance, high storm losses will be followed by one of two possible price/quantity regimes: (i) A regime where prices are high enough to reflect the frequency and severity of losses in storm-battered regions, in a manner that compensates insurers' for the risks they take on; or (ii) A regime of controlled prices where insurance is scarce because government refuses to acknowledge the fact that insurers cannot provide protection for people and property in high-risk places at prices that do not reflect the risk. [34] A third option — the increased socialization of insurance by the creation and expansion of state sponsored insurance and re-insurance facilities in affected states — is a likely short-term response to the problem of the declining availability and affordability of insurance in the aftermath of large hurricane losses. However, these mechanisms turn out to be so freighted with well known incentive and fiscal problems that they have generally not become long term solutions to the inevitability of expensive insurance in regions where private insurers must cope with substantial exposures to large hurricane losses. Though it would seem obvious, enormous effort continues to be expended in trying to escape the reality that where places, things, and people are expensive to insure, insurance will be expensive

[34] These remarks should not be interpreted as either implicit or explicit support for a federal government role in providing reinsurance in cases of natural disasters. The considerations raised in Jaffee and Russell's [25] excellent economic analysis of arguments for and against a natural catastrophe reinsurance scheme must still be explored in far more detail before a reasonable conclusion about the feasibility — to say nothing about the *desirability* — of a natural catastrophe fund is reached. Our purpose here in assessing the resilience of the insurance industry in the face of a series of large hurricane losses is to assess the financial consequences of extreme weather events. How a natural catastrophe reinsurance system would alter the protective or efficiency properties of insurance markets remains an open question.

5. Concluding Remarks

In this paper, we have sought to explore the nature and consequences of scientific uncertainty in the matter of global climate dynamics for insurers. Contemporary climate science is an impressive intellectual endeavor that has revealed much about the complex dynamics of the Earth's climate system, enough to put us on notice that climate change is a natural phenomenon, increasingly driven and amplified by human activity. Indeed, climate science has confirmed the expanding contribution of anthroprogenic climate change to the gradual and millennial changes in our planet's climate system that are the source of weather, as well as the more alarming possibility that human activity might lead to abrupt climatic change that radically alters the nature of the Earth's weather. Yet, climate science offers few hints about how, or when, the Earth's climate system will change, much less how these changes might affect weather patterns in particular regions, or the frequency or severity of extreme weather events like hurricanes, tornadoes, heat waves, torrential rains or even rising sea levels. Advances in climate science have shown us that the Earth's weather systems are incredibly complex and mathematically chaotic, and unlikely to fully reveal their internal mechanisms to scientists for some time to come. For now, what we know for certain is that our planet's climate is changing, that this change could lead to an increase in the frequency and severity of dangerous weather at some time in the future, and that institutions charged with the pricing, management, and mitigation of risk should pay close attention to scientific developments.

As part of our presentation, we explored the profitability consequences of massive losses from one form of extreme weather — a string of Quartet-scale storms striking the United States, as well as the prospect of a Katrina-scale storm combined with a mass terror attack on the scale of 9/11 — on the theory that prudence in the face of scientific uncertainty warrants consideration of worst-case scenarios. The results of this econometric approach to exploring the relation between insurer profitability and extreme weather suggest a high level of macro-resilience for the insurance industry, in the sense that the system — with its current operating procedures — can withstand a series of severe shocks. Yet, as our discussion above suggests, the industry's recovery mechanism involves a series of price and quantity adjustments, along with regulatory and public policy developments, that will alter the availability and affordability of insurance, along with insurers methods for managing claims in the face of disaster. A detailed, micro-economic analysis of the insurance industry's response to the challenges posed by climate change involves a much more tightly focused consideration of the interaction of particular perils — tornadoes, flood, hurricanes, heat — in particular regions, with specific regulatory approaches in light of state and federal public policy constraints, as well as the financial conditions facing insurers. Of course, the whole issue of how insurers deal with gradual, as opposed to abrupt, climate change is itself a vast subject in its own right, not least because abrupt climate change threatens to make it difficult if not impossible for companies to use their accumulated knowledge about past risks and losses to predict what may be an utterly different weather future.

The good news in all of this — aside from the fact that climate science gives little support to the idea that a string of weather catastrophes is more likely to befall us in the immediate future than over the past few decades or even longer — is that we have time to apply climate science, economics, risk management, and (lest we forget) common sense to the problem of pricing, managing and mitigating extreme weather risk. This study is the first in a series of projects that will explore various aspects of extreme weather and insurance in the shadow of climate change. Ultimately, our objective is to increase the industry's store of intellectual capital in the face of an uncertain, but potentially vast, challenge to its capacity to protect people and property.

Appendix A: Reduced-Scale Climate Models

Present-day efforts to confront and, ultimately, manage the prospect of anthropogenic climate change have lead researchers to propose a broad range of analytical frameworks and methodologies for characterizing and evaluating the various dimensions of the problem. In recent years, it has become commonplace and fashionable for economists, policy analysts, and climate researchers to focus their efforts on the development of a class of models commonly referred to as *integrated assessment* models of global climate change. Integrated assessment models (IAMs) are characterized by their broad-based, comprehensive approach to the analysis of the climate change problem. IAMs seek to represent the most salient features of the climate change problem, and are typically comprised of analytically tractable linkages between (i) models of atmospheric, oceanic, and biological processes; (ii) models of the global climate system; and (iii) models of the socio-economic processes that influence, and are affected by, climatic change. [35] In the years to come, insurers and underwriters will need to embrace these methods, and make them a part of the way they structure and evaluate their underwriting and risk management decisions with regard to extreme weather risks.

As discussed in Section 2, global energy balance models (EBMs) constitute the simplest means by which to model the climate system of the Earth. Historically, such models have played an important role in our understanding of the various components and processes that influence climatic change. The earliest EBMs date back to the late 1960s, beginning with the work of Budyko [7] and Sellers [39] demonstrating that equator-to-pole energy transport and radiation streams are fundamental processes of the global climate system.

The fundamental principle underlying all EBMs is that the *incoming* and the *outgoing* radiation for the globe is—in the long run—balanced. In more formal terms, the rate of change of the surface temperature, T, with time, t, is represented as the difference between *net incoming* and *net outgoing* radiant energies. This relationship between time, temperature, and radiant energies can be stated informally as follows:

$$K \frac{\Delta T}{\Delta t} = R\downarrow - R\uparrow, \tag{1}$$

where K is the "thermal inertia" or *heat capacity* [36] of the system, and $R\downarrow$ and $R\uparrow$ are the incoming and outgoing radiation fluxes, respectively.

[35] For insightful discussions on current approaches to climate change related integrated assessment modeling, see, e.g., Dowlatabadi [11], Parson [36], and Toth [43].

[36] The *heat capacity* of a body is defined as the ratio of the amount of heat energy that a body is supplied with to its corresponding temperature rise.

Eq. (1) serves as the conceptual basis for a variety of EBMs. Schneider and Mass [38], for example, propose a one-box time-dependent globally averaged model of the Earth's climate system. The model they put forth is *zero-dimensional*, in that the Earth is treated as a single point in space, characterized by a global-mean surface temperature whose value at time t is denoted $T(t)$. The model is formally specified in terms of a global energy balance equation, with heat storage expressed in terms of solar energy absorbed minus infrared energy emitted to space. If we let $\Delta T(t) = T(t+h) - T(t)$ denote the change in *global-mean surface temperature* during the finite time interval $[\,t,\, t+h)$, and define the time-step $\Delta t = h$, then the *global energy balance* for this model is given by

$$K \lim_{h \to 0} \frac{\Delta T(t)}{h} \;=\; K\,\frac{dT(t)}{dt} \;=\; Q\,[1 - \alpha(T(t))] -\, R_{ir}\!\uparrow(T(t)), \tag{2}$$

where K is the heat capacity coefficient, Q is the annually averaged solar radiation received by the earth (a constant with respect to both time and temperature), $\alpha(T(t))$ is the *planetary albedo*,[37] and $R_{ir}\!\uparrow(T(t))$ is the outgoing infrared radiation to space.

In order to render Eq. (2) more amenable to analysis, we linearize $\alpha(T(t))$ and $R_{ir}\!\uparrow(T(t))$ as follows [38,46]:

$$\alpha(T(t)) = a + b\,T(t), \tag{3}$$
$$R_{ir}\!\uparrow(T(t)) = x + y\,T(t). \tag{4}$$

Typically, the real-valued coefficients a, b, x, and y in Eqs. (3) and (4) are treated as empirically-determined constants that account for the greenhouse effect of clouds, water vapor, and CO_2 [30].

Eq. (4) provides a conceptually simple means by which to combine the effects of surface emissivity and atmospheric transmisivity. For our purposes here, it is useful to modify this equation slightly. Specifically, in order to explore the response of the one-box model to external CO_2 forcing, we generalize Eq. (4) by lumping together the effects of increasing atmospheric CO_2 concentrations due to anthropogenic CO_2-equivalent emissions into the coefficient x. If we treat anthropogenic CO_2 as an exogenously specified variable that is dependent on time, but not on $T(t)$, then Eq. (4) can be rewritten as

$$R_{ir}\!\uparrow(t, T(t)) \;= x(t) + y\,T(t), \tag{5}$$

[37] *Planetary albedo* is defined as the ratio of reflected to incident radiation, and provides a measure of the *reflectivity* of the earth's surface and its atmosphere.

where the function $R_{ir} \uparrow$ is now defined on a domain that consists of both time, t, and global mean surface temperature, $T(t)$. Intuitively, Eq. (5) states that the outgoing infrared radiation to space can, in principle, change over time, even if global-mean temperature remains constant.

Now, substituting Eqs. (3) and (5) into Eq. (2) yields

$$
\begin{aligned}
K\,\frac{dT(t)}{dt} &= Q[1-(a+b\,T(t))] \;-\; [x(t)+y\,T(t)] \\
&= (1-a)Q - (b\,Q\;+y)T(t) \;-\; x(t).
\end{aligned} \tag{6}
$$

In order to estimate the impact of rising CO_2 concentrations on climate, relative to some pre-industrial baseline which we denote by t_0, at time $t = t_0$, we assume that the system is in a state of *climatic equilibrium*; that is, the time derivative $dT(t)/dt$ evaluated at time $t = t_0$ is equal to zero. At equilibrium, we are able to establish the following initial condition for Eq. (6):

$$
(b\,Q + y)T(t_0) = (1-a)Q - x(t_0). \tag{7}
$$

For $t \geq t_0$, let $T(t) \ = T(t_0) + [T(t) - T(t_0)]$. Also, to simplify notation, let

$$
\tau(t) = T(t) - T(t_0)
$$

denote the difference between global-mean surface temperature T at times t and t_0, respectively. Eq. (6) can now be written as

$$
\begin{aligned}
K\,\frac{dT(t)}{dt} &= K\,\frac{d}{dt}\,[T(t_0)+\tau(t)] \;=\; K\,\frac{d\tau(t)}{dt} \\
&= (1-a)Q - (b\,Q+y)T(t_0) \;-\; (b\,Q+y)\tau(t) \;-\; x(t).
\end{aligned} \tag{8}
$$

Now, substituting Eq. (7) into Eq. (8) yields

$$
\begin{aligned}
K\,\frac{d\tau(t)}{dt} &= (1-a)Q - [(1-a)Q - x(t_0)] \;-\; (b\,Q+y)\tau(t) \;-\; x(t) \\
&= x(t_0) \;-\; x(t) \;-\; (b\,Q+y)\tau(t).
\end{aligned} \tag{9}
$$

By defining $F(t) = x(t_0) - x(t)$ and $\lambda = y + b\,Q$, Eq. (9) can be expressed as

$$
K\,\frac{d\tau(t)}{dt} = F(t) - \lambda\,\tau(t), \tag{10}
$$

where $F(t)$ denotes the change (from equilibrium) of that part of the time-dependent outgoing longwave radiation that is independent of temperature. Intuitively, we recognize that as concentrations of CO_2 in the atmosphere increase, the values that $x(t)$ takes on decrease and $F(t) > 0$, which agrees with our intuition about the effects of increased CO_2 in the atmosphere.

In terms of a finite time interval $[\,t,\, t+h)$, for some time-step $h > 0$, when h is small, Eq. (10) can be approximated by

$$K\,[\tau(t+h) - \tau(t)] \;\approx\; h\,[F(\xi) - \lambda\,\tau(\xi)], \tag{11}$$

for any $t \leq \xi < t+h$. Now, if we choose $h = 1$ and let $\xi = t$, then Eq. (11) becomes

$$K\,[\tau(t+1) - \tau(t)] \;\approx\; F(t) - \lambda\,\tau(t),$$

which gives rise to

$$\tau(t+1) \;\approx\; \tau(t) \;+\; \frac{1}{K}\,[F(t) - \lambda\,\tau(t)]. \tag{12}$$

Equivalently, Eq. (12) can be expressed as

$$\tau(t) \;\approx \tau(t-1) + \;\frac{1}{K}\,[F(t-1) - \lambda\,\tau(t-1)]. \tag{13}$$

It bears mentioning that if we choose $\xi = t+h-\epsilon$, for small ϵ satisfying $h > \epsilon > 0$, then, letting $h = 1$, Eq. (11) becomes

$$K\,[\tau(t) - \tau(t-1)] \;\approx\; [F(t-\epsilon) - \lambda\,\tau(t-\epsilon)],$$

in which case

$$\tau(t) \;\approx\; \tau(t-1) + \;\frac{1}{K}\,[F(t-\epsilon) - \lambda\,\tau(t-\epsilon)].$$

As $\epsilon \to 0$, we obtain

$$\tau(t) \;\approx\; \tau(t-1) + \;\frac{1}{K}\,[F(t) - \lambda\,\tau(t)].$$

Thus, from a purely analytical vantage point, there exists some degree of flexibility as to whether F and τ are treated as contemporaneous or lagged variables.

The climate model given by Eq. (13) is concerned only with the atmosphere of the Earth. Most atmospheric processes, however, are strongly coupled to the Earth's oceans. In what follows, we extend the model presented above to include ocean-atmosphere interactions.

The globally averaged two-box model that we consider here was originally developed by Schneider and Thompson [38], and versions of it are used by Nordhaus [35] and others in several recent integrated assessments of global climate change.

In this globally averaged model, the ocean-atmosphere system is represented by two "boxes" or layers: one layer for land and another for the world ocean. The upper box consists of a land fraction, f_L, and is characterized by a globally and annually averaged temperature, $T(t)$; the lower box consists of an ocean fraction, $1-f_L$, and is characterized by a globally and annually averaged temperature, $T^*(t)$. Each of these layers is assumed to be internally well-mixed. As in the case of the one-box model, the two-box model is driven by external solar forcing, Q — the absorbed portion of which is scaled by the planetary albedo $\alpha(T(t))$ — and emits infrared radiation, $R_{ir}\!\uparrow(t, T(t))$, to space. The *heat transfer rate* between the upper and the lower box is proportional to the *volume rate*, $\dot{V}(t)$, of water exchange between the two boxes.

The global energy balance for the two-box model is formally specified by the following system of equations:

$$K_1 \frac{dT(t)}{dt} = Q\,[1-\alpha(T(t))] \;-\; R_{ir}\!\uparrow(t, T(t)) - \frac{c_w}{\sigma_g}\,\dot{V}(t)\,[T(t) - T^*(t)]\,, \tag{14}$$

$$K_2 \frac{dT^*(t)}{dt} = \frac{c_w}{\sigma_g}\,\dot{V}(t)\,[T(t) - T^*(t)]\,, \tag{15}$$

where K_1 and K_2 are the thermal inertias for the upper and lower box, respectively, c_w is the volumetric heat capacity of water, and σ_g is the global surface area. [38]

The thermal inertias K_1 and K_2 are given by

[38] We note that the two-box model described by Eqs. (14) and (15) can be viewed intuitively as a generalization of the one-box model developed above. Specifically, the model can be specified in terms of the weighted sum

$$K_1 \frac{dT(t)}{dt} + K_2 \frac{dT^*(t)}{dt} = Q\,[1-\alpha(T(t))] - R_{ir}\!\uparrow(t, T(t)),$$

where $K_2 \frac{dT^*(t)}{dt}$ is defined by Eq. (15).

$$K_1 = \frac{c_w}{\sigma_g} V, \tag{16}$$

$$K_2 = \frac{c_w}{\sigma_g} V^*, \tag{17}$$

where V and V^* are the water-equivalent volumes of the upper and the lower box, respectively. Note that in this model, the water-equivalent volumes are fixed with respect to both time and temperature.

As in the case of the one-box model, we are ultimately interested in examining the behavior of the two-box model to external, anthropogenic CO_2 forcing. Looking, first, at Eq. (14), we use the linearized forms for $\alpha(T(t))$ and $R_{ir}\uparrow(t, T(t))$ given previously by Eqs. (3) and (5), respectively, to rewrite Eq. (14) as

$$\begin{aligned} K_1 \frac{dT(t)}{dt} &= Q\,[1-(a+b\,T(t))] - [x+y\,T(t)] \\ &\quad - \frac{c_w}{\sigma_g}\dot{V}(t)\,[T(t)-T^*(t)] \\ &= (1-a)Q - (b\,Q+y)T(t) - x(t) \\ &\quad - \frac{c_w}{\sigma_g}\dot{V}(t)\,[T(t)-T^*(t)]\,. \end{aligned} \tag{18}$$

As before, the variable t_0 denotes some pre-industrial baseline relative to which we wish to measure climatic change. At time t_0, we assume that the system is in a state of climatic equilibrium. At equilibrium, two conditions obtain: first, the time derivative $dT(t)/dt$ evaluated at time $t = t_0$ is equal to zero; second, the surface temperature at time $t = t_0$, $T(t_0)$, is equal to the ocean temperature at time $t = t_0$, $T^*(t_0)$. Thus, at time $t = t_0$, in equilibrium, Eq. (18) yields

$$(b\,Q+y)T(t_0) = (1-a)Q - x(t_0). \tag{19}$$

Now, let $\tau(t) = T(t) - T(t_0)$ denote the difference between global-mean surface temperature at times t and t_0, respectively; similarly, let $\tau^*(t) = T^*(t) - T^*(t_0)$ denote the difference between ocean temperature at times t and t_0, respectively. Using these definitions, the two-box model specified by Eqs. (18) and (15) becomes

$$\begin{aligned} K_1 \frac{dT(t)}{dt} &= K_1 \frac{d}{dt}[T(t_0)+\tau(t)] \;=\; K_1 \frac{d\tau(t)}{dt} \\ &= (1-a)Q - (b\,Q+y)[T(t_0)+\tau(t)] - x(t) \\ &\quad - \frac{c_w}{\sigma_g}\dot{V}(t)\,[T(t_0)-T^*(t_0)+\tau(t)-\tau^*(t)] \\ &= (1-a)Q - (b\,Q+y)T(t_0) - (b\,Q+y)\tau(t) - x(t) \end{aligned}$$

$$
\begin{aligned}
&\quad - \frac{c_w}{\sigma_g} \dot{V}(t) \left[T(t_0) - T^*(t_0) + \tau(t) - \tau^*(t) \right], \\
K_2 \frac{dT^*(t)}{dt} &= K_2 \frac{d}{dt} \left[T^*(t_0) + \tau^*(t) \right] = K_2 \frac{d\tau^*(t)}{dt} \\
&= \frac{c_w}{\sigma_g} \dot{V}(t) \left[T(t_0) - T^*(t_0) + \tau(t) - \tau^*(t) \right].
\end{aligned}
$$

Since, in equilibrium, $T(t_0)$ equals $T^*(t_0)$, these two equations can be rewritten as

$$
\begin{aligned}
K_1 \frac{d\tau(t)}{dt} &= (1-a)Q - (b\,Q + y)T(t_0) \; - \; (b\,Q + y)\tau(t) \; - \; x(t) \\
&\quad - \frac{c_w}{\sigma_g} \dot{V}(t) \left[\tau(t) - \tau^*(t) \right], \qquad (20) \\
K_2 \frac{d\tau^*(t)}{dt} &= \frac{c_w}{\sigma_g} \dot{V}(t) \left[\tau(t) - \tau^*(t) \right]. \qquad (21)
\end{aligned}
$$

At equilibrium, Eq. (19) obtains, in which case Eq. (20) becomes

$$
\begin{aligned}
K_1 \frac{d\tau(t)}{dt} &= (1-a)Q - \left[(1-a)Q - x(t_0) \right] \; - \; (b\,Q + y)\tau(t) \; - \; x(t) \\
&\quad - \frac{c_w}{\sigma_g} \dot{V}(t) \left[\tau(t) - \tau^*(t) \right] \\
&= x(t_0) \; - \; x(t) \; - \; (b\,Q + y)\tau(t) - \frac{c_w}{\sigma_g} \dot{V}(t) \left[\tau(t) - \tau^*(t) \right]. \qquad (22)
\end{aligned}
$$

As before, letting $F(t) = x(t_0) - x(t)$ and $\lambda = y + b\,Q$, Eq. (22) can be rewritten as

$$
K_1 \frac{d\tau(t)}{dt} = F(t) \; - \; \lambda\,\tau(t) \; - \; \frac{c_w}{\sigma_g} \dot{V}(t) \left[\tau(t) - \tau^*(t) \right]. \qquad (23)
$$

In this equation, $F(t)$ is again interpreted as the change — from a specified baseline — of that portion of the outgoing longwave radiation, $R_{ir}\!\uparrow$, that is dependent upon time, but is independent of temperature.

In this representation, we are interested in exploring the effects that upper and lower box mixing have on the climate variable of interest, namely, the upper box temperature, $T(t)$. Following Broecker [6] and Schneider and Thompson [38], we use the following parameterization for upper and lower box mixing:

$$
\dot{V}(t) = \frac{V^*}{\nu_d}, \qquad (24)
$$

where V^* is defined as before, and ν_d is the *ventilation time* of the world deep ocean. Substituting Eqs. (24) and (17) into Eqs. (23) and (21), the system of equations for the two-box model becomes

$$K_1 \frac{d\tau(t)}{dt} = F(t) - \lambda\,\tau(t) - \frac{K_2}{\nu_d}\,[T(t) - T^*(t)]\,, \tag{25}$$

$$K_2 \frac{d\tau^*(t)}{dt} = \frac{K_2}{\nu_d}\,[T(t) - T^*(t)]\,. \tag{26}$$

As in the case of the one-box model, for computational purposes, it is useful to express the two-box model in finite-difference form. To this end, consider a finite time interval $[\,t,\, t+h)$, for some nonzero time-step h. For small values of h, Eqs. (25) and (26) are approximated by

$$K_1\,[\tau(t+h) - \tau(t)] \approx h\left(F(\xi) - \lambda\,\tau(\xi) - \frac{K_2}{\nu_d}\,[\tau(\xi) - \tau^*(\xi)]\right),$$

$$K_2\,[\tau^*(t+h) - \tau^*(t)] \approx h\left(\frac{K_2}{\nu_d}\,[\tau(\xi) - \tau^*(\xi)]\right),$$

for any $t \leq \xi < t+h$. If we let $\xi = t$, and make our time-step unity, then this system of equations becomes

$$\tau(t+1) \approx \tau(t) + \frac{1}{K_1}\left(F(t) - \lambda\,\tau(t) - \frac{K_2}{\nu_d}\,[\tau(t) - \tau^*(t)]\right),$$

$$\tau^*(t+1) \approx \tau^*(t) + \frac{1}{K_2}\left(\frac{K_2}{\nu_d}\,[\tau(t) - \tau^*(t)]\right).$$

Equivalently, if we let $t = t - 1$, then the two-box model can be expressed as

$$\begin{aligned}\tau(t) \approx \tau(t-1) + \frac{1}{K_1}\Bigg(&F(t-1) - \lambda\,\tau(t-1)\\ &- \frac{K_2}{\nu_d}\,[\tau(t-1) - \tau^*(t-1)]\Bigg),\end{aligned} \tag{27}$$

$$\tau^*(t) \approx \tau^*(t-1) + \frac{1}{\nu_d}\,[\tau(t-1) - \tau^*(t-1)]\,. \tag{28}$$

Eqs. (27) and (28) can be represented succinctly in matrix form as

$$\begin{pmatrix} \tau(t) \\ \tau^*(t) \end{pmatrix} = \begin{pmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{pmatrix} \begin{pmatrix} \tau(t-1) \\ \tau^*(t-1) \end{pmatrix} + \frac{1}{K_1} \begin{pmatrix} F(t-1) \\ 0 \end{pmatrix}, \tag{29}$$

where

$$\begin{aligned} \Gamma_{11} &= -\frac{1}{K_1}\left(\lambda + \frac{K_2}{\nu_d}\right), \\ \Gamma_{12} &= \frac{K_2}{K_1 \nu_d}, \\ \Gamma_{21} &= \frac{1}{\nu_d}, \\ \Gamma_{22} &= -\frac{1}{\nu_d}. \end{aligned}$$

In this structural representation, we note that thermal forcing due to changes in atmospheric CO_2 concentrations is decoupled from the climatic variables, and is treated as an *exogenous* input to the system.

In order to simplify notation, we define a (2×1) column vector $\mathbf{y}_t$ and a (2×2) *parameter matrix* $\mathbf{\Gamma}$ as

$$\mathbf{y}_t \equiv \begin{pmatrix} \tau(t) \\ \tau^*(t) \end{pmatrix},$$

and

$$\mathbf{\Gamma} \equiv \begin{pmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{pmatrix},$$

where the matrix elements Γ_{ij} are defined as above. In addition, we define a (2×1) vector $\mathbf{u}_t$ as

$$\mathbf{u}_t \equiv \begin{pmatrix} \frac{1}{K_1} F(t) \\ 0 \end{pmatrix}.$$

Using the above definitions, system (29) can be expressed succinctly as

$$\mathbf{y}_t = \mathbf{\Gamma}\, \mathbf{y}_{t-1} + \mathbf{u}_{t-1}. \tag{30}$$

Intuitively, we recognize that Eq. (30) holds true for all values of t, in which case

$$\mathbf{y}_{t-1} = \mathbf{\Gamma}\,\mathbf{y}_{t-2} + \mathbf{u}_{t-2}. \tag{31}$$

If we let $(\mathbf{\Gamma})^k$ denote the k^{th} power of the parameter matrix $\mathbf{\Gamma}$ and, in addition, define $(\mathbf{\Gamma})^0$ to be the identity matrix, then substituting Eq. (31) into Eq. (30) yields

$$\begin{aligned}\mathbf{y}_t &= \mathbf{\Gamma}(\mathbf{\Gamma}\,\mathbf{y}_{t-2} + \mathbf{u}_{t-2}) + \mathbf{u}_{t-1}\\ &= (\mathbf{\Gamma})^2\,\mathbf{y}_{t-2} + \mathbf{\Gamma}\,\mathbf{u}_{t-2} + \mathbf{u}_{t-1}.\end{aligned}$$

By induction, it is easily verified that

$$\mathbf{y}_t = (\mathbf{\Gamma})^t\,\mathbf{y}_0 + \sum_{j=1}^{t} (\mathbf{\Gamma})^{j-1}\,\mathbf{u}_{t-j}. \tag{32}$$

Eq. (32) provides a computationally simple means by which to compute numerical values of the vector time series $\mathbf{y}_t$.

Long-term climate predictions are a central component of integrated assessments of global climate change, which seek to explore the socio-economic impacts associated with climate change in tandem with considerations about the science of climate change. The computational costs entailed in running large-scale climate models makes their use in portfolio management and underwriting contexts a practical impossibility. The reduced-scale models outlined above provide risk assessors and underwriters with an instrumental basis for balancing the need for scientific adequacy and realism, on the one hand, against the need for computational efficiency and model transparency, on the other.

Appendix B: An Econometric Analysis of P/C Industry Resilience

A number of single equation models of the link between the rate of return on P/C surplus and various measures of hurricane activity have been estimated (using standard econometric estimation techniques [39]), with some surprising results. One model of particular interest was of the form

$$r_t^i = \beta_0 + \beta_1 H_t + \beta_2 Z_t + \beta_3 r_t^{10} + \beta_4 r_{t-1}^i + \beta_5 D_t^{9/11} + \beta_6 PremGrow_t + \varepsilon_t,$$

where

$r_t^i =$ return on equity for insurers in year t;

$H_t =$ number of hurricanes with billion dollar losses in year t (2005 dollars);

$Z_t =$ index of mean intensity of hurricanes in year t;

$r_t^{10} =$ interest rate on ten year Treasury bonds;

$D_t^{9/11} =$ binary variable for 9/11 terrorist attack $(1 = 9/11$ attack);

$PremGrow_t =$ growth rate of net written premiums in year t;

$\varepsilon_t =$ standard normal i.i.d. error term.

The data used to estimate this equation were derived from the NOAA hurricane data base (hurricane number and strength data, from 1980–2005), the Economic Report of the President (Treasury bond rates), and the Insurance Information Institute (annual P/C rate of return data from 1950–2005). The index (Z) for hurricane intensity is the average category number for hurricanes based on the Saffir/Sampson scale.

The equation above consistently yielded statistically insignificant estimates for the number and intensity of hurricanes in any given year — both when lagged P/C returns were included (Column 1) and excluded (Column 2), where Table 3 contains the relevant information on coefficient values, corrected t-statistics (in parentheses), the standard error of the estimate (SEE), the value of the Durbin h-statistic (h), and the estimate of the first-order serial correlation coefficient for the OLS error (ρ) for various model specifications that we rejected. As noted in the text of the paper, other specifications included separate variable for hurricanes of different power — Categories 1 through 5 — as both dummy variables and as cardinal measures of storm power. Again, none of these variables were statistically significant.

[39] See, e.g., Hayashi [18].

Variable	1	2	3	4
Constant	3.254	6.021	3.027	4.045
	(1.727)	(3.730)	(1.652)	(2.309)
H_t	0.855	0.694	0.418	*****
	(1.460)	(1.226)	(1.061)	*****
Z_t	-0.463	-0.374	*****	0.016
	(-1.027)	(-0.857)	*****	(0.053)
r_t^{10}	0.235	0.261	0.298	0.155
	(1.365)	(1.564)	(1.332)	(0.980)
r_{t-1}	0.304	*****	0.298	0.292
	(2.746)	*****	(3.118)	(3.095)
D_t	-9.335	-9.960	-9.178	-9.711
	(-4.108)	(-4.534)	(-4.134)	(-4.432)
$PremGrow_t$	0.223	0.167	0.241	0.230
	(3.120)	(2.172)	(3.126)	(2.921)
SEE	2.101	2.530	2.079	2.035
DW	*****	1.689	*****	*****
Durbin h	7.490	*****	7.341	7.524
ρ	0.037	*****	0.280	0.232
Time Period	1980-2005	1980-2005	1980-2005	1980-2005

Table 3
Various specifications of the P/C return on equity equation.

The preferred equation (on statistical grounds) is

$$r_t^i = \beta_0 + \beta_3 r_t^{10} + \beta_4 r_{t-1}^i + \beta_5 D_t^{9/11} + \beta_6 PremGrow_t + \varepsilon_t,$$

which is estimated as

$$\begin{array}{l} r_t^i = 0.479 + 0.043 r_t^{10} + 0.625 r_{t-1}^i - 8.351 D_t^{9/11} + 0.323 PremGrow_t \\ \qquad (0.323) \quad (0.187) \quad\quad (4.79) \quad\quad (-2.328) \quad\quad (3.238) \end{array}$$

over the period 1953–2005 (t-statistics in parentheses), with SEE $= 3.107$, $\rho = 0.443$, and Durbin $h = 6.559$. The correlation matrix associated with this equation is presented in Table 4.

	r_{t-1}^i	r_t^{10}	$D_t^{9/11}$	$PremGrow_t$
r_{t-1}^i	1			
r_t^{10}	0.668	1		
$D_t^{9/11}$	-0.033	-0.042	1	
$PremGrow_t$	0.072	0.338	0.038	1

Table 4
Correlation matrix for econometric analysis.

Note that the lagged value of insurers' return on equity is highly correlated with the current value of the 10-year Treasury bond rate, indicating a high degree of collinearity between these two variables, which accounts for the low value of the t-statistic on the Treasury bond rate variable. In addition, the Treasury bond rate has a moderate degree of correlation with net premium growth.

References

[1] Contributions of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. In *Climate Change 2001: The Scientific Basis*, J. Houghton et al., Eds. Cambridge University Press.

[2] Financial risks of climate change. Tech. rep., Association of British Insurers, London, 2005.

[3] AMERICAN METEOROLOGICAL SOCIETY COUNCIL AND UCAR BOARD OF TRUSTEES. *The Changing Atmosphere — Challenges and Opportunities*, Bulletin of the American Meteorological Society ed., 1988.

[4] ARRHENIUS, S. On the influence of carbonic acid in the air upon the temperature of the ground. *Philosophical Magazine 41* (1896), 237–276.

[5] BOLIN, B., HOUGHTON, J., AND FILHO, L. *Radiative Forcing of Climate Change: The 1994 Report of the Scientific Assessment Working Group of IPCC, Summary for Policymakers*. Intergovermental Panel on Climate Change, 1994.

[6] BROECKER, W. A revised estimate for the radiocarbon age of North Atlantic deep water. *Journal of Geophysical Research 84* (1979), 3218–3226.

[7] BUDYKO, M. I. The effect of solar radiation variations on the climate of the Earth. *Tellus 21*, 5 (1969), 611–619.

[8] CESS, R. D., ET AL. Uncertainties in carbon dioxide radiative forcing in atmospheric general circulation models. *Science 262* (1993), 1252–1255.

[9] CHAN, J. C., AND LIU, S. L. Global warming and western North Pacific typhoon activity from an observational perspective. *Journal of Climate 17* (2004), 4590–4602.

[10] CUBASCH, U., AND CESS, R. D. Processes and modelling. In *Climate Change: The IPCC Scientific Assessment*, J. T. Houghton, G. J. Jenkins, and J. J. Ephraums, Eds. Cambridge University Press, New York, 1990, pp. 69–92.

[11] DOWLATABADI, H. Integrated assessment models of climate change: An incomplete overview. *Energy Policy 23*, 4–5 (1995), 289–296.

[12] EMANUEL, K. The dependence of hurricane intensity on climate. *Nature 326* (1987), 483–485.

[13] EMANUEL, K. Increasing destructiveness of tropical cyclones over the past 30 years. *Nature 436* (2005), 686–688.

[14] FOURIER, J. B. Temperature du globe terrestre et des espace planetaires. In *Fourier, J. B., Ouvres*, G. Darboux, Ed., vol. 2. Gauthier-Villars, Paris, 1888, pp. 97–125.

[15] FREE, M., BISTER, M., AND EMANUEL, K. Potential intensity of tropical cyclones: comparison of results from radiosonde and reanalysis data. *Journal of Climate 17* (2004), 1722–1727.

[16] HANSEN, J., ET AL. Global climate changes as forecast by Goddard Institute for Space Studies three-dimensional model. *Journal of Geophysical Research 93*, D8 (August 1988), 9341–9364.

[17] HARRABIN, R. Consensus grows on climate change. *BBC News* (March 2006).

[18] HAYASHI, F. *Econometrics*. Princeton University Press, Princeton, NJ, 2000.

[19] HENDERSON-SELLARS, A., ET AL. Tropical cyclones and global climate change: A post-IPCC assessment. *Bull. Amer. Meteor. Soc. 79* (1998), 9–38.

[20] HOUGHTON, J. T., CALLANDER, B. A., AND VARNEY, S. K., Eds. *Climate Change 1992: The Supplementary Report to the IPCC Scientific Assessment*. Cambridge University Press, New York, 1992.

[21] HOUGHTON, J. T., JENKINS, G. J., AND EPHRAUMS, J. J., Eds. *Climate Change: The IPCC Scientific Assessment*. Cambridge University Press, New York, 1990.

[22] IDSO, S. B., BALLING, R. C., AND CERVENY, R. S. Carbon dioxide and hurricanes: Implications of Northern Hemisphere warming for Atlantic/Caribbean storms. *Meteorology and Atmospheric Physics 42* (1990), 259–263.

[23] IDSO, S. B., AND MITCHELL, J. F. The search for CO_2 / trace gas greenhouse warming. *Theoretical and Applied Climatology 40* (1989), 101–102.

[24] JACOBY, H. D., AND PRINN, R. G. Uncertainty in climate change policy analysis. Tech. Rep. 1, MIT Joint Program on the Science and Policy of Global Change, December 1994.

[25] JAFFEE, D., AND RUSSELL, T. Markets under stress: The case of extreme event insurance. In *Economics for an Imperfect World: Essays in Honor of Jospeh E. Stiglitz*, R. Arnott et al., Eds. MIT Press, Cambridge, MA, 2003.

[26] KNUTSON, T. R., AND TULEYA, R. E. Impact of CO_2-induced warming on simulated hurricane intensity and precipitation: Sensitivity to the choice of climate model and convective parameterization. *Journal of Climate 17*, 18 (2004), 3477–3495.

[27] LANDSEA, C. W., ET AL. Atlantic basin hurricanes: Indices of climatic change. *Climatic Change 42* (1999), 89–129.

[28] LINDZEN, R. S. Climate dynamics and global change. Tech. Rep. 28, Center for Global Change Science, Massachusetts Institute of Technology, 1994.

[29] MANABE, S., AND STOUFFER, R. Century-scale effects of increased atmospheric CO_2 on the ocean-atmosphere system. *Nature 364* (1993), 215–218.

[30] MCGUFFIE, K., AND HENDERSON-SELLERS, A. *A Climate Modelling Primer*, third ed. John Wiley & Sons, New York, 1987.

[31] MICHAELS, P. J., KNAPPENBERGER, P. C., AND LANDSEA, C. W. Comments on: "Impacts of CO_2-induced warming on simulated hurricane intensity and precipitation: Sensitivity to the choice of climate model and convective scheme". *Journal of Climate* (December 2005), 5179–5182.

[32] MILLS, E., ROTH, R., AND LECOMTE, E. Availability and affordability of insurance under climate change: A growing challenge for the united states. Tech. rep., CERES, 2005.

[33] MORGAN, M. G., AND KEITH, D. W. Subjective judgments by climate experts. *Environmental Science and Technology 29*, 10 (1995), 468–476.

[34] NATIONAL ACADEMY OF SCIENCES. *Policy Implications of Greenhouse Warming*. National Academy Press, Washington, D.C., 1992.

[35] NORDHAUS, W. D. *Managing the Global Commons: The Economics of Climate Change*. MIT Press, Cambridge, Massachusetts, 1994.

[36] PARSON, E. A. Integrated assessment and environmental policy making: In pursuit of usefulness. *Energy Policy 23*, 4–5 (1995), 463–475.

[37] ROYER, J. F., ET AL. A GCM study of impact of greenhouse gas increase on the frequency of occurrence of tropical cyclones. *Climate Dynamics 38* (1998), 307–343.

[38] SCHNEIDER, S. H., AND THOMPSON, S. L. Atmospheric CO_2 and climate: Importance of the transient response. *Journal of Geophysical Research 86*, C4 (1981), 3135–3147.

[39] SELLERS, W. D. A global climate model based on the energy balance of the Earth-atmosphere system. *Journal of Applied Meteorology 8* (1969), 392–400.

[40] SHINE, K. P., ET AL. Radiative forcing of climate. In *Climate Change: The IPCC Scientific Assessment*, J. T. Houghton, G. J. Jenkins, and J. J. Ephraums, Eds. Cambridge University Press, New York, 1990, pp. 41–68.

[41] STOUFFER, R., ET AL. Century-scale effects of increased atmospheric CO_2 on the ocean-atmosphere system. *Nature 367* (1994), 634–640.

[42] SUGI, M., NODA, A., AND SATO, N. Influence of the global warming on tropical cyclone climatology: An experiment with the JMA global model. *J. Meteor. Soc. Japan 80* (2002), 249–272.

[43] TOTH, F. L. Practice and progress in integrated assessments of climate change. *Energy Policy 23*, 4–5 (1995), 253–267.

[44] UZAWA, H. *Economic Analysis of Common Social Capital*. Cambridge University Press, New York, 2005.

[45] VALVERDE, JR, L. J. Integrated assessment modeling: A simultaneous equations model of the global climate system. In *Comparative Risk Assessment and Environmental Decision-Making*, I. Linkov and A. Ramadan, Eds. Kluwer Academic Publishers, 2004.

[46] WARREN, S. G., AND SCHNEIDER, S. H. Seasonal simulation as a test for uncertainties in the parameterization of a Budyko-Sellars zonal climate model. *Journal of Atmospheric Science 36* (1979), 1377–1391.

[47] WEBSTER, P. J., ET AL. Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science 309* (2005), 1844–1846.