Comparing impacts across climate models

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In this paper we combine a climate-forecasting model, COSMIC, with a global impact model, GIM, to compare the market impacts of climate change projected by 14 general circulation models. Given a specific date (2100), carbon dioxide concentration (612 ppmv), and global temperature sensitivity (2.5 °C), predicted impacts to economies are calculated using climate-response functions from Experimental and Cross-sectional evidence. The Cross-sectional impact model predicts small global benefits across all climate models, whereas the Experimental impact model predicts a range from small benefits to small damages. High-latitude countries are less sensitive to temperature increases than low-latitude countries because they are currently cool. Uniform global temperature changes overestimate global damages because they underestimate the benefits in polar regions and overestimate the damages in tropical regions compared to the GCM predictions.

1. Introduction

Two tools have recently been developed to project anthropogenically induced climate changes and their impacts. COSMIC [25] uses the global-mean surface temperature calculated by a simple climate/ocean model to scale in time the geographical patterns of changes in surface temperature and precipitation simulated by any of 14 General Circulation models (GCMs) to generate country-specific climate projections. GIM [19] combines country-specific climate projections, market-sector data, and climate-response functions to predict market impacts from warming by sector and nation. In this paper we combine these two tools to compare the projections of the 14 GCMs whose results are included in COSMIC. This large number of GCMs was selected to illustrate the variation across models. We thought it important to show more than one climate-response function again to illustrate differences. However, it is important that policy analysts understand that the scenarios do not demonstrate all possible sources of uncertainty. For example, we do not explore the effect of alternative baseline emission scenarios, variations in temperature sensitivity, alternative time lags due to the ocean, and alternative climate-response functions. Instead, the scenarios emphasize the new insights from making country-level associations between climate forecasts and impacts. The integration of GCMs and country-level impact models provides a new mechanism for comparing GCM forecasts and for understanding the distribution of impacts across the earth.

There are many links in the chain from carbon dioxide emissions to climate projections [13]. We know a lot about each step and yet each step remains a source of uncertainty. Alternative assumptions about the path of the economy alter emissions over space and time. The carbon cycle determines how these emissions affect concentrations in the atmosphere. Changes in carbon dioxide and other manmade greenhouse gases alter the net radiative flux at the top of the atmosphere, which constitutes a radiative forcing of the climate system. Changes in temperature at different heights in the atmosphere will in turn affect clouds and ice, either compounding or reducing this radiative effect, generating global temperature sensitivity. Finally, the ocean will gradually respond to temperature change, warming at different levels over time, creating a dynamic response that may take decades to centuries to play out. COSMIC combines a simple climate/ocean model with the geographical distributions of the changes in surface temperature and precipitation simulated by 14 GCMs. Assuming that the geographic climate distributions from each model can be scaled by the global-mean surface temperature change, COSMIC predicts country-specific climate projections for each GCM.

GIM ties the country-specific projections of changes in surface temperature and precipitation to predictions of market impacts by sector and country. First, GIM projects what the future economy will look like at the time of the impact. Models of each sector must reference baseline projections of economic activity for that sector in order to calculate future climate impacts. For example, agriculture is predicted to grow more slowly than the rest of the economy, cooling will grow relative to warming in space conditioning, and the world economy will be about ten times larger by 2100. Second, the climate-response function of each sector must be predicted. Unfortunately, this is one of the weakest links in global-warming research. It is very uncertain how the entire earth will respond to any given climate change. Climate-response functions have been estimated only for market effects, that is, impacts to economic sectors [18]. Although these projections are presented as point estimates, they are clearly uncertain. We present two projections that come from entirely different empirical approaches to illustrate the range of uncertainty. Even this is an understatement of the true level of uncertainty since we have very little empirical information about the impacts of climate change on developing countries. Finally, the climate-response functions in this paper have been calibrated only for the United States. The climate-response functions for the quality of life such as ecological changes, human health, and aesthetic impacts, are still under development; hence, they are not yet included in GIM. Thus, the market impacts discussed in this paper cannot be compared directly against estimates of all impacts such as in [4,22,32].

Since climate itself is changing very slowly, it is extremely difficult to measure across time the sensitivity of market sectors to climate change. The literature has consequently resorted to two alternative approaches, Experimental and Cross-sectional. The Experimental approach constructs process-based simulation models from carefully conducted scientific experiments. Using laboratory-controlled settings, experiments are run on crops, trees, and other subjects to determine their sensitivity to temperature, precipitation, and carbon dioxide. Simulation models are constructed from the experimental evidence to predict what will happen in the aggregate. The Cross-sectional approach uses evidence from alternative locations to make predictions. By comparing one area with a warmer site, the Cross-sectional approach is able to discern what would happen to that place in the long run if it warmed. Both approaches have strengths and weaknesses. The Experimental approach is able to isolate the impact of each element through laboratory controls, while the Cross-sectional approach is subject to unwanted variation from factors it fails to control. This advantage of the Experimental approach leads to a weakness. The controls imposed by the Experimental approach may eliminate important responses by subjects, that is, adaptations that limit damages and enhance benefits. Since the Cross-sectional approach includes responses people have already made to where they live, the Cross-sectional approach captures adaptation. Because the two methods have different strengths and weaknesses, and both are highly uncertain, it is prudent to include both methods in impact analysis.

In this paper we explore a set of future conditions to compare the impacts calculated for the changes in surface temperature and precipitation simulated by 14 GCMs. We utilize both Experimental and Cross-sectional climate-response functions to evaluate the climate projections based on each of the GCMs. By examining the impacts, we can gain new insights into which projected climate changes are important, which are consistent across the GCMs, and how best to describe these projections for the globe. We focus on impacts in 2100 to obtain a long-run, but still relevant, perspective. We assume that humankind commits itself to a maximum equivalent CO_2 concentration of 750 ppmv, which implies a carbon dioxide concentration of 612 ppmv in 2100 [13]. We assume that global population has doubled to 10 billion and that the global gross domestic product (GDP) is 217 trillion, a ten-fold increase. Finally, we assume that global temperature sensitivity is 2.5 °C, that is, the equilibrium global-mean surface temperature increase for a CO_2 doubling is 2.5 °C.

In the next section we describe various features of COSMIC and GIM in detail. In section 3 we describe the aggregate results for each GCM. In section 4 we analyze these alternative results to explain which features of the climate projections generate large impacts, which projections are consistent, and how to aggregate climate forecasts across the earth from an impacts perspective.

2. COSMIC and GIM

2.1. COSMIC

Analyses of the impacts of anthropogenically induced climate changes require time-dependent scenarios of the geographical distributions of these climate changes. If the anthropogenic emissions of greenhouse gases (GHGs) and sulfur dioxide (SO_2) and the sensitivity of the climate system were known, the best-possible method of constructing geographical scenarios of climate change would be to perform climate-change simulations with coupled atmosphere–ocean general circulation models (CGCMs), from pre-industrial time into the future. However, the future anthropogenic emissions of GHGs and CO_2 are highly uncertain (e.g., [30]), as is the radiative forcing due to sulfate (SO_4) aerosol created in the atmosphere from the emitted SO_2 [13]. Thus it is computationally impossible to perform with a CGCM the multitude of climate-change simulations required to span the ranges of possible emission scenarios, climate sensitivities and sulfate radiative forcing (ΔF_{SO_4} (1990)). Accordingly a simpler, computationally practicable method of constructing these numerous geographical scenarios of climate change is needed.

The method of scenario construction we employ in the Country Specific Model for Intertemporal Climate (COSMIC) was developed by [23] and further refined at the Climatic Research Unit, University of East Anglia, Norwich, UK [14], and used in the scenario generation code, SCENGEN [15]. The method has also been used elsewhere [24,25,29,30]. An atmospheric GCM with a mixed-layer ocean (AGC/MLO) model is used to simulate a control (con) equilibrium climate and the equilibrium experiment (exp) climate for an enhanced CO_2 concentration. The geographical distribution of CO_2-induced equilibrium climate change for any climatic quantity, $Q(\lambda, \varphi, m)$, where λ and φ are the longitude and latitude of the AGC/MLO model's grid cells and m is the calendar month, is then calculated and normalized by the corresponding change in annual global-mean surface-air temperature, $\overline{T}_{\text{exp}} - \overline{T}_{\text{con}}$,

$$\Delta Q_{\text{N}}(\lambda, \varphi, m) = \frac{Q_{\text{exp}}(\lambda, \varphi, m) - Q_{\text{con}}(\lambda, \varphi, m)}{\overline{T}_{\text{exp}} - \overline{T}_{\text{con}}}. \qquad (1)$$

The change in annual global-mean surface-air temperature,

$$\Delta\overline{T}(y) = \overline{T}(y) - \overline{T}(y_0), \qquad (2)$$

from some pre-industrial time, y_0 (1765), to the present is calculated with our energy-balance–climate/upwelling–diffusion–ocean model [28] using the historical radiative forcing of the Intergovernmental Panel on Climate Change [13] and then into the future for a prescribed climate-change scenario and a prescribed climate sensitivity, G. The changes in annual global-mean surface-air temperature relative to a reference year, y_{ref} ($=$ 1990), are then calculated from

$$\delta\overline{T}(y) = \overline{T}(y) - \overline{T}(y_{\text{ref}}) = \Delta\overline{T}(y) - \Delta\overline{T}(y_{\text{ref}}). \qquad (3)$$

The time-dependent geographical distributions of monthly climate change in year y relative to y_{ref} for each climate-change scenario of equivalent CO_2 concentration[1] and prescribed climate sensitivity are then determined from

$$\delta Q(\lambda,\varphi,y,m) = \delta\overline{T}(y)\Delta Q_{\text{N}}(\lambda,\varphi,m), \qquad (4)$$

the normalized pattern of greenhouse-gas-induced climate change being taken to be the same as the pattern of CO_2-induced climate change, $\Delta Q_{\text{N}}(\lambda,\varphi,m)$. Finally, the monthly climatic quantities in year y are obtained from

$$Q(\lambda,\varphi,y,m) = Q_{\text{obs}}(\lambda,\varphi,y_{\text{ref}},m) + \delta Q(\lambda,\varphi,y,m), \qquad (5)$$

where $Q_{\text{obs}}(\lambda,\varphi,y_{\text{ref}},m)$ are the observed climatic quantities for month m of the reference year or period containing the reference year.

In COSMIC the geographical distributions of the normalized changes in monthly mean surface-air temperature and precipitation, $\Delta Q_{\text{N}}(\lambda,\varphi,m)$, can be chosen for any of the 14 GCMs listed in table 1. The changes in annual global-mean surface-air temperature, $\delta\overline{T}(y)$, can be calculated by COSMIC for any of 7 main scenarios of future concentrations of greenhouse gases [39], each for low, medium and high sulfate aerosol emission rates[2] [39], as well as for two ways (proposed by [13] and [37]) of stabilizing the CO_2 concentration at either 350, 450, 550, 650 or 750 ppmv. Each calculation can be performed for a wide range of values of G and ΔF_{SO_4} (1990). COSMIC calculates the country-specific annual cycles of surface-air temperature and precipitation rate for 177 countries, as well as the global-mean sea-level rise, and is available gratis on compact disk.[3]

[1] The amount of CO_2 required to give the same radiative forcing as all the greenhouse gases together.

[2] In Version 1 of COSMIC, the sulfate aerosol burden influences only $\delta\overline{T}(y)$, that is, no account is taken of the geographical distribution of climate change due to the sulfate aerosol. The latter will be included in Version 2 of COSMIC.

[3] To request a no-cost license contact: Larry J. Williams; Electric Power Research Institute; 3412 Hillview Avenue; E-mail: ljwillia@epri.com; fax: (650) 855-2950.

2.2. GIM

GIM is a spreadsheet model that begins with a country-specific set of climate changes and then predicts market impacts. A separate model is designed for each sensitive market sector: agriculture, forestry, energy, water, and coastal structures. A separate calculation is made for each sector and country that combines the change in climate, sector data, and a climate-response function. This leads to calculations of damages or benefits by sector and country. Quality-of-life effects such as changes in ecosystems, health, and aesthetic losses are not included in this version of the model as climate-response functions for these effects are not yet available.

The current version of GIM responds to annual temperature and precipitation. Future versions of the model will move to seasonal climate variables to gain more detailed insight into climate impacts. Annual climate by country is one of the inputs to the model. These projections are obtained from COSMIC for each GCM.

For each country, key parameters of each sector are collected. For example, area of cropland, area of forestland, and length of coastline provide important insights into agriculture, forestry, and coastal structures, respectively. Gross Domestic Product (GDP) by country is also a key in several sectors. As GIM becomes more sophisticated, additional parameters will be collected for each country.

The heart of GIM is its climate-response functions. Earlier impact research predicted impacts from a limited set of climate scenarios. Examining individual scenarios becomes cumbersome when it is important to evaluate a large number of scenarios and when one evaluates a path of climate change. Consequently, the literature had begun to develop climate-response functions, descriptions of how impacts change within a sector as climate changes [18]. Many integrated assessment models have climate-response functions to measure damages, given a path of climate change [12,16,21,22]. Unfortunately, many of these response functions were invented by the authors or were fit to very limited observations (for example, current conditions and doubling of greenhouse gases). In this paper, we rely upon climate-response functions based on empirical research [20]. In that study, over a dozen of the leading impact researchers did empirical studies of each of the climate-sensitive sectors of the US economy. There were four key elements in this new research: inclusion of efficient adaptation, broad sectoral estimates, dynamic analysis when appropriate, and use of future economic conditions.

The research relied upon the two major alternative methods of measuring the response to climate. Several studies relied upon the Experimental method, which begins with carefully controlled laboratory studies and uses these to construct simulation models. The remainder of the studies relied on Cross-sectional evidence. By comparing farms and households in cool versus warm locations, one can estimate how people have adapted to their resident climates and how they may react as these climates change in the

Table 1
GCM model simulations: global annual averages for doubling the pre-industrial carbon dioxide concentration.

Acronym	Institution	ΔT (°C)	ΔP (%)	Reference
BMRC	Bureau of Meteorology Research Center	2.11	2.38	[10]
CCC	Canadian Climate Centre	3.50	4.00	[2,3,17]
GF30	Geophysical Fluid Dynamics Laboratory (R30 run)	4.00	8.3	[35,36]
GFDL	Geophysical Fluid Dynamics Laboratory (first run)	4.00	8.3	[35,36]
GFQF	Geophysical Fluid Dynamics Laboratory (Q-flux run)	4.00	8.30	[35,36]
GISS	Goddard Institute for Space Studies	4.20	11.00	[7–9]
HEND	Henderson-Sellers using CCM1 at NCAR	2.50	5.60	[11]
OSU	Schlesinger and Zhao at Oregon State University	2.40	7.80	[26]
POLD	Pollard and Thompson-GENESIS with dynamic sea-ice	2.27	3.13	[31]
POLS	Pollard and Thompson-GENESIS with static sea-ice	2.27	3.13	[31]
UIUC	Schlesinger at University of Illinois at Urbana-Champaign	3.37	5.53	[28]
UKMO	United Kingdom Meteorological Office	5.20	15.00	[38]
WANG	Wang et al. at State University of New York at Albany and NCAR[a]	3.90	6.90	[33]
WASH	Washington and Meehl using CCM1 at NCAR	4.82	4.75	[34]

[a] NCAR is the National Center for Atmospheric Research.

Table 2
Aggregate impacts in 2100 by GCM model experimental responses (billions of 1990 $/year).

GCM	Continent[a]							
	Total	Africa	Asia	LatAm	WEur	Comm	NAm	Ocean
BMRC 54	−112	−31	−67	1	224	48	−9	
CCC	28	−139	−52	−87	9	250	62	−13
GF30	210	−79	−9	−30	14	245	83	−16
GFDL	203	−100	−8	−37	12	267	81	−12
GFQF	134	−113	−1	−49	13	224	78	−17
GISS	45	−103	−86	−59	15	217	73	−13
HEND	−69	−163	−103	−73	9	216	66	−21
OSU	−33	−111	−157	−45	13	209	68	−10
POLS	147	−134	40	−92	10	230	114	−22
POLD	163	−103	−77	−44	20	270	112	−14
UIUC	−139	−186	−161	−97	10	223	85	−12
UKMO	27	−139	−97	−62	14	245	82	−17
WANG	−29	−143	−145	−72	18	239	90	−17
WASH	25	−123	−90	−55	12	219	79	−18
AVERAGE	**55**	**−125**	**−70**	**−62**	**12**	**234**	**80**	**−15**

[a] The continents above are Africa, Asia, Latin America, Western Europe, the former Soviet Union and Eastern bloc, North America, and Oceania.

long run. The strength of the Experimental method is that it can isolate climate effects from other factors in the environment. Further, it can explore the effect of factors that are not yet evident in the environment, such as higher levels of carbon dioxide. The weakness of the approach is that experiments are designed to control responses, both environmental and human. Adaptations that ecological systems and people make to climate change are suppressed, thereby exaggerating the damages and reducing the benefits from warming. The Cross-sectional approach is able to capture efficient adaptations because the method compares systems currently adapted to different climates. For example, the farm in a cool place is compared to a farm in a warm place, given all the adaptations that farmers have made to where they live. This advantage of Cross-sectional evidence comes at a cost. Cross-sectional studies are vulnerable to unmeasured factors that may be correlated with climate. If these factors are not taken into account, they

Table 3
Aggregate impacts in 2100 by GCM model Cross-sectional responses (billions of 1990 $/year).

GCM	Continent[a]							
	Total	Africa	Asia	LatAm	WEur	Comm	NAm	Ocean
BMRC	150	−10	32	−3	2	100	29	−1
CCC	152	−18	31	−6	5	108	33	−2
GF30	185	−5	35	3	6	106	41	−2
GFDL	184	−9	31	2	5	114	42	−1
GFQF	165	−12	35	0	6	98	41	−3
GISS	131	−15	17	−7	7	94	38	−2
HEND	97	−28	8	−10	5	95	32	−4
OSU	116	−15	0	−3	6	93	37	−1
POLS	173	−16	39	−7	6	101	53	−4
POLD	175	−10	21	−2	8	112	48	−2
UIUC	98	−31	−1	−14	5	99	42	−2
UKMO	136	−21	16	−5	6	104	39	−3
WANG	119	−22	1	−9	7	102	43	−3
WASH	143	−13	22	−2	5	96	38	−3
AVERAGE	**145**	**−16**	**21**	**−5**	**6**	**102**	**40**	**−2**

[a] The continents above are Africa, Asia, Latin America, Western Europe, the former Soviet Union and Eastern bloc, North America, and Oceania.

can be confused with climate effects, thereby leading to misleading results. This is not a problem for the carefully controlled experimental studies. Consequently, the Experimental and Cross-sectional methods complement each other well, and we rely upon both of them in this study.

The climate-response functions in these studies were quadratic in temperature. That is, the response function indicated a hill-shaped relationship between impacts and temperature. This is an essential feature of the model and explains many of the results in this paper. Countries that are currently cooler than optimal are predicted to benefit from warming. Countries that happen to be warmer than optimal are predicted to be harmed by warming. Although the quantitative measures shown in the paper remain highly uncertain, these qualitative insights are likely to be robust.

3. Results

Combining the projections of COSMIC and GIM, one can examine the impacts from a wide set of climate models. COSMIC provides a consistent set of conditions so that the scenario, global temperature sensitivity, and ocean dynamics are the same. Given these identical conditions, one can then study the alternative distributional patterns predicted by each GCM and examine their effect on impacts. Although there have been a number of GCM comparisons conducted by atmospheric scientists, these studies focused on climate projections, not the resulting impacts [6]. Previous comparisons have consequently not been able to identify which aspects of these projections are important, what impacts do these GCMs consistently agree upon, which aspects lead to a wide range of impacts, and how best to aggregate climate projections across the earth.

To compare the 14 GCMs using a consistent set of starting conditions, we make a number of assumptions. First, we assume that carbon emissions are on a global path consistent with reaching a maximum of 750 ppmv [13]. Second, we examine the impacts in 2100. Given the IPCC path specified above, carbon dioxide will reach 612 ppmv by 2100. Third, we specify a global temperature sensitivity of 2.5 °C. The model predicts a global-average temperature of 2.21 °C by 2100. Fourth, we assume that the economy grows according to medium projections so that global GDP is $217 trillion by 2100. Given these assumptions, we calculate the country-specific climate outcomes according to each of the 14 GCMs in COSMIC. These climate changes are then used to predict impacts by market sector for each country.

In tables 2 and 3 we present continental estimates of aggregate market impacts for each of the 14 GCMs using the Experimental and Cross-sectional climate-response functions, respectively. Compared to the size of the economy in 2100 ($217 trillion), the market effects are small. Global net impacts have a broad range across GCMs using the Experimental climate-response functions: from $139 billion of damages to $210 billion of benefits, with an average of $55 billion of benefits. The Cross-sectional climate-response functions imply a narrower range of impacts across GCMs: from $97 to $185 billion of benefits, with an average of $145 billion of benefits a year. The Experimental climate-response functions are more steeply hill-shaped and thus they respond more sharply to temperature increases in the polar and tropical regions. This explains why the Experimental results are more sensitive to the variety of GCM projections.

The results are also quite different across countries. First, the GCMs generally agree that temperature change increases with latitude. The GCMs also agree that precipitation changes will not be uniform, although the precipitation projections are not consistent across the GCMs. However, the impact models suggest that the magnitude of impacts will depend not only on the changes in temperature and precipitation, but also on the base conditions in each country. Countries that are already hot or dry will be more vulnerable to warming. Countries that are cold, in contrast, are likely to benefit from warming. These initial conditions lead to different outcomes across countries.

The results indicate that there will be large benefits from warming in the Former Communist bloc (the former Soviet Union and Eastern Bloc countries). The benefits in this region almost offset losses throughout the tropics in the Experimental results. The Soviet benefits account for two-thirds of the net global benefits in the Cross-sectional results. The results also suggest that there will be large benefits in North America and small benefits in Western Europe. The critical factor that these benefiting countries have in common is that they are currently cool so that warming is helpful. The Experimental model predicts sizeable damages from warming in Africa, Latin America, Oceania, and often Asia because these areas are currently already hot. In contrast, the Cross-sectional model predicts that Africa, Oceania, and Latin America will suffer only modest damages because of the compensating effects of carbon fertilization and adaptation, and that Asia will likely benefit.

It is interesting to compare this geographic pattern against the predictions of other authors. Tol predicts benefits for more polar countries and damages for low latitude countries as in this analysis [32]. However, both Fankhauser and Nordhaus predict more uniform damages across the entire world [4,22]. It appears that both of these latter studies fail to fully account for initial climate conditions in predicting warming impacts in a country. Because it is important, future integrated assessment models will need to do a better job of integrating geographically specific climate predictions and impacts.

The most important market impact from warming is agricultural. According to the Experimental results, agriculture was responsible for average global benefits of $88 billion, compared to total net benefits of only $55 billion. The Cross-sectional results were similar; agriculture would provide average benefits of $163 billion compared to total net market benefits of $145 billion. Forestry was also perceived as being beneficial, contributing an additional $20 and $29 billion in the Experimental and Cross-sectional results, respectively. The remaining sectors were expected to generate net damages. Water damages were expected to average $32 billion, energy damages were expected to be about $9 billion, and coastal impacts were anticipated to be $6 billion.

In addition to generating the largest expected effect, agriculture also explains most of the variation both across countries and across the GCMs. The standard error of aggregate market impacts across the 14 GCMs is $101 billion in the Experimental results and $54 billion in the Cross-sectional results. The standard error for agricultural impacts is $94 billion in the Experimental results and $52 billion in the Cross-sectional results. Agriculture is the source of most of the variation across models. In comparison, water has a standard error of only $9 billion and energy only $4 billion.

The three GCMs that predict the largest benefits in tables 2 and 3; GF30, GFDL, and POLD, all predict large increases in temperature at high latitudes and small increases at low latitudes. The benefits in the Communist bloc countries and North America are consequently higher and the damages in Latin America and Africa are lower. In contrast, the three GCMs that predict the greatest damages or smallest benefits in tables 2 and 3; HEND, OSU, and UIUC, predict more uniform temperature changes; relatively high values for low latitudes and relatively modest increases at high latitudes. The benefits to the polar countries are consequently smaller and the damages in the tropical countries are higher.

The variability of estimated global impacts that result from differences in the GCM climate forecasts can be seen in more detail with the maps shown in figures 1 and 2. Figure 1 shows annual percentage changes in GDP as calculated by the Experimental climate-response functions driven by different climate-change projections. The GCMs used to prepare the three maps were chosen to represent the maximum, average, and minimum impacts. There are several ways in which the maximum and minimum impact maps could be chosen. Total global market welfare losses (shown in tables 2 and 3) could be used. This would result in a measure mainly dependent on the countries with the largest GDPs. An alternative would be to compare area- or population-weighted percent GDP changes. In some sense this would result in maps with the most/least red, and would place the most weight on countries with the largest areas or populations. Instead, we chose a method that weights each country equally, independent of GDP, area, or population. This method ranks 14 possible maps according to the sum of percentage changes in GDP across all 177 countries included in the GIM model.

The maximum-impact map in both figures 1 and 2 resulted from using the UIUC GCM climate simulation. This GCM generated larger impacts because it predicts relatively more warming in the tropics than the other models. The minimum-impact map (again for both figures) was produced with the POLD simulation. This GCM predicts more benefits because it predicts relatively more warming for more polar countries and less warming in the tropics. The top map in figure 1 and 2 is the minimum impact map and the maximum map is at the bottom of the figures. The middle map shows the average impact, calculated by averaging the impacts estimated by each of the 14 climate models used in this analysis.

The most striking feature of figures 1 and 2 is the similarity between maps going from top (minimum impact) to bottom (maximum impact). Of course, the choice of "bins" shown in the legend strongly affects the main features of the maps. Nevertheless, these maps support the points

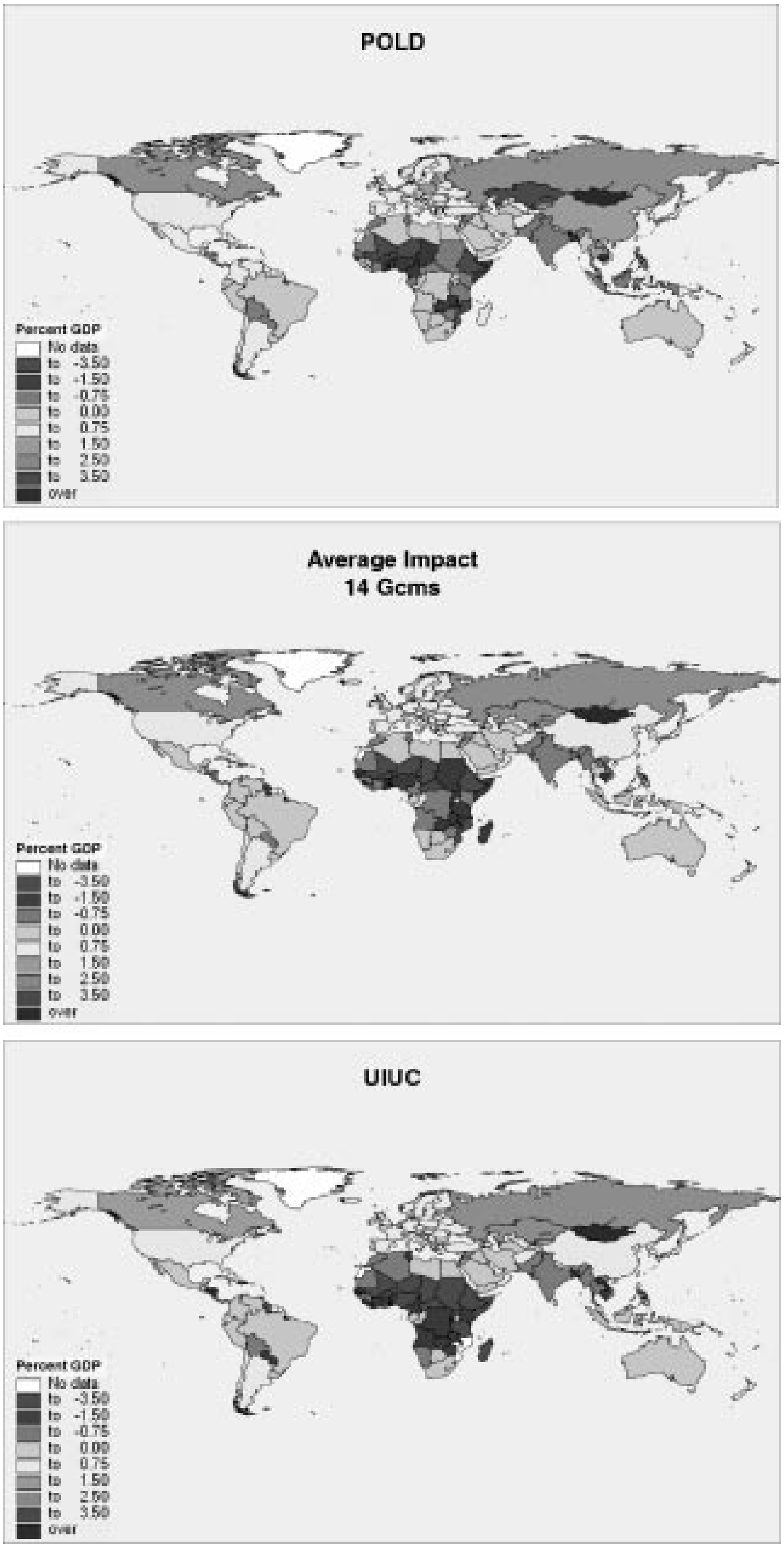

Figure 1. Range of impacts calculated using Experimental climate-response functions. The POLD model produced smaller impacts than most other Gcms. The UIUC model led the high impact end of the group.

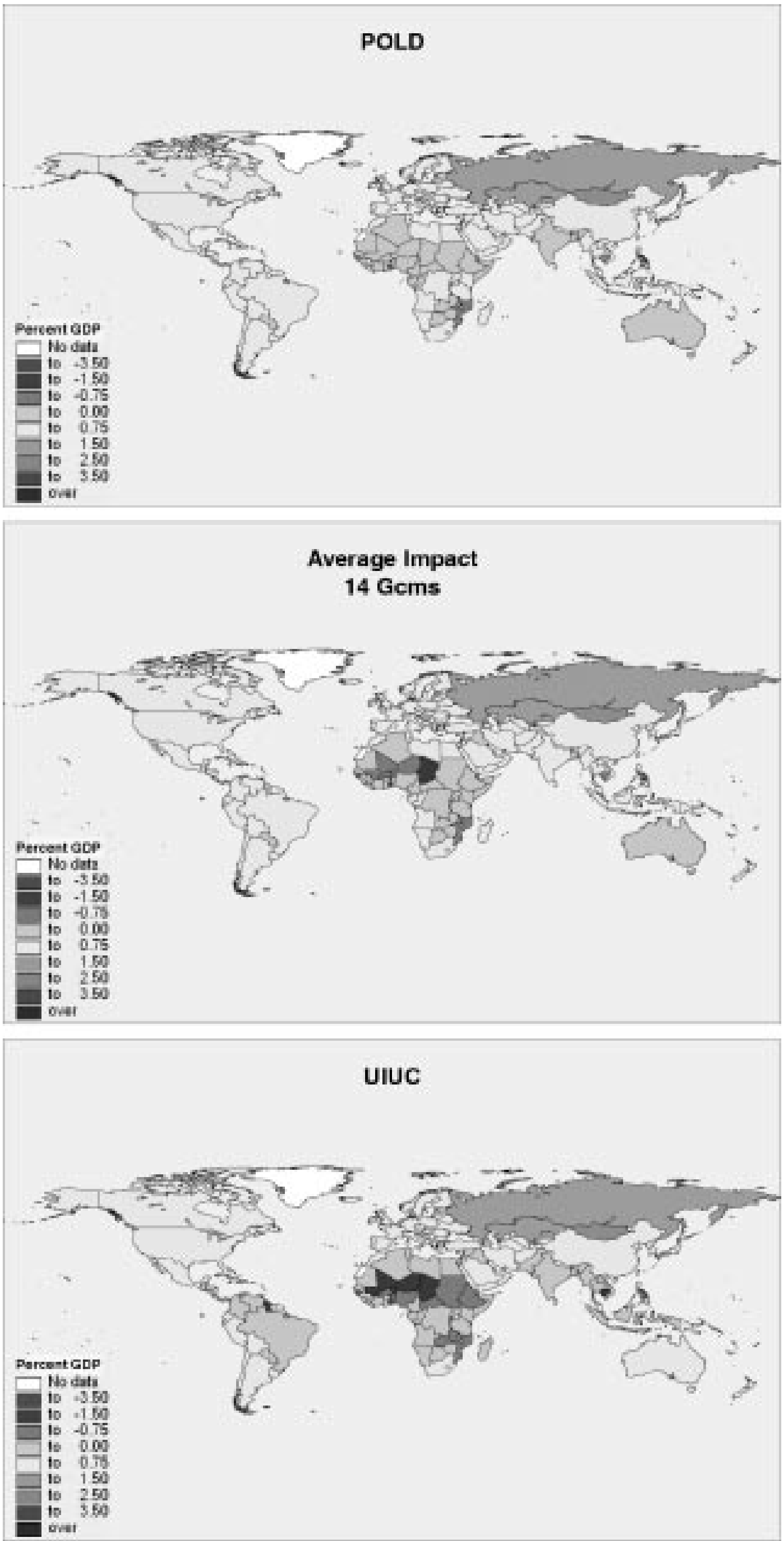

Figure 2. Range of impacts calculated using Cross-sectional climate-response functions. The POLD model produced smaller impacts than most other Gcms. The UIUC model led the high impact end of the group.

Table 4
Regressions of aggregate impacts on average global climate change.[a]

$\text{Impact}_{\text{Experimental}}$	$= 720$	$-\ 341\ T_{\text{Pop}}$	$+\ 1711\ P_{\text{Pop}}$
	186	77	687
$\text{Impact}_{\text{Experimental}}$	$= 809$	$-\ 317\ T_{\text{Area}}$	$+\ 639\ P_{\text{Area}}$
	423	163	917
$\text{Impact}_{\text{Cross-sectional}}$	$= 375$	$-\ 109\ T_{\text{Pop}}$	$+\ 206\ P_{\text{Pop}}$
	62	26	228
$\text{Impact}_{\text{Cross-sectional}}$	$= 381$	$-\ 94\ T_{\text{Area}}$	$-\ 29\ P_{\text{Area}}$
	126	49	274

[a] Dependent variable is net global market effects for 2100 in billions of 1990$. Climate variables measure the aggregate change in temperature and precipitation weighted by either population or area. The standard errors are below the regression equation.

evident in tables 2 and 3. Developing countries in the tropics are likely to be harmed by expected climate change, while the developed countries, and transition economies, in temperate and northern climates will see a net improvement in the market sectors that are most responsive to climate changes.

Although it has become customary to average temperature increases across the entire globe when reporting global changes, global impacts are more sensitive to the population-weighted average change. We compare two alternative aggregations of temperature and precipitation across nations. The area measure weights climate in countries by total area. The population measure weights all climate changes by the number of people in each country. Countries with more people get more weight. Table 4 reports regressions of global net impacts across the 14 models on aggregate temperature and precipitation using the two alternative weights. The population-weighted measure of both temperature and precipitation is statistically more significant and can explain a greater fraction of the variance of global impacts across the climate models. Population-weighted temperature and precipitation changes are better predictors of impacts than land-weighted averages. This insight is likely to apply to national averages as well. Weighting grids by population can give a better estimate of the average temperature change than weighting grids by area.

Table 4 provides another key insight. The coefficient on temperature change is negative and significant in all the models. Although the net impacts of climate change are beneficial relative to an unchanged state, the models imply that higher temperatures are harmful. There are two explanations of this result. First, the climate-response function for temperature is hill-shaped, not linear. Starting from a cool climate, warming is beneficial at first. However, as warming continues, more countries exceed the optimum and warming becomes increasingly harmful. By 2100, all the GCMs predict that the unweighted global temperature change will exceed 2 °C at which point further warming is harmful. Second, changes in precipitation and carbon dioxide are beneficial. Thus the overall net impact of all the changes is beneficial, even though the marginal effect of additional temperature is harmful by 2100.

Table 5
Regressions of regional impacts on regional climate change (Experimental).[a]

$\text{Impact}_{\text{Africa}}$	$= 44$	$-\ 86\ T_{\text{Pop}}$	$+\ 287\ P_{\text{Pop}}$
	6	3	14
$\text{Impact}_{\text{Asia}}$	$= 214$	$-\ 157\ T_{\text{Pop}}$	$+\ 994\ P_{\text{Pop}}$
	103	42	332
$\text{Impact}_{\text{LatAmer}}$	$= 42$	$-\ 59\ T_{\text{Pop}}$	$+\ 357\ P_{\text{Pop}}$
	15	8	34
$\text{Impact}_{\text{WEur}}$	$= 9$	$-\ 1\ T_{\text{Pop}}$	$+\ 93\ P_{\text{Pop}}$
	5	2	11
$\text{Impact}_{\text{Soviet}}$	$= 99$	$+\ 39\ T_{\text{Pop}}$	$+\ 235\ P_{\text{Pop}}$
	41	13	76
$\text{Impact}_{\text{NAmer}}$	$= 84$	$-\ 7\ T_{\text{Pop}}$	$+\ 216\ P_{\text{Pop}}$
	28	7	42
$\text{Impact}_{\text{Oceania}}$	$= 6$	$-\ 11\ T_{\text{Pop}}$	$+\ 28\ P_{\text{Pop}}$
	11	6	17

[a] Dependent variable is regional impacts in 2100 in billions of 1990$. Regional climate change is average change in region.

Table 6
Regressions of regional impacts on regional climate change (Cross-sectional).[a]

$\text{Impact}_{\text{Africa}}$	$= 37$	$-\ 26\ T_{\text{Pop}}$	$+\ 38\ P_{\text{Pop}}$
	1	1	3
$\text{Impact}_{\text{Asia}}$	$= 110$	$-\ 44\ T_{\text{Pop}}$	$+\ 103\ P_{\text{Pop}}$
	27	11	85
$\text{Impact}_{\text{LatAmer}}$	$= 34$	$-\ 21\ T_{\text{Pop}}$	$+\ 44\ P_{\text{Pop}}$
	3	2	7
$\text{Impact}_{\text{WEur}}$	$= 8$	$-\ 1\ T_{\text{Pop}}$	$+\ 25\ P_{\text{Pop}}$
	2	1	4
$\text{Impact}_{\text{Soviet}}$	$= 56$	$+\ 14\ T_{\text{Pop}}$	$+\ 60\ P_{\text{Pop}}$
	16	5	29
$\text{Impact}_{\text{NAmer}}$	$= 51$	$-\ 5\ T_{\text{Pop}}$	$+\ 54\ P_{\text{Pop}}$
	10	3	20
$\text{Impact}_{\text{Oceania}}$	$= 5$	$-\ 4\ T_{\text{Pop}}$	$+\ 7\ P_{\text{Pop}}$
	3	1	4

[a] Dependent variable is regional impacts in 2100 measured in billions of 1990$. Regional climate change is average change in region.

The sensitivity of each sector to climate is not uniform across all regions. Tables 5 and 6 display the regional sensitivity. These sensitivities were calculated by regressing the Experimental and Cross-sectional impacts on the population-weighted climate measures for each region. North America, Western Europe, and the Soviet bloc all have positive or small negative temperature coefficients because they are currently cool. In contrast, Africa, Asia, and Latin America have large negative temperature coefficients because they are currently hot. The resources each continent possesses determine the size of the coefficients. Asia has large coefficients because it has the most people, whereas Oceania has few people and thus small coefficients throughout. Tables 5 and 6 also reveal that the temperature sensitivity of the Experimental results is greater in magni-

Table 7
Market impacts from uniform climate change.[a]

Measure	Continent[b]							
	Total	Africa	Asia	LatAm	WEur	Comm	NAm	Ocean
				Experimental				
Average GCM	59	−125	−69	−60	14	234	80	−15
Area	−130	−145	−154	−82	15	187	67	−19
Population	−72	−123	−120	−67	15	172	65	−15
				Cross-sectional				
Average GCM	146	−16	21	−4	6	102	40	−2
Area	95	−21	2	−12	7	87	36	−3
Population	114	−15	12	−7	7	81	36	−2

[a] Impacts are measured in billions of 1990 $/year. The area-weighted uniform temperature change is 2.49 °C with a precipitation increase of 5.5% and the population-weighted uniform temperature change is 2.21 °C, with a precipitation increase of 5.2%.

[b] The continents are Africa, Asia, Latin America, Western Europe, the former Soviet Union and Eastern bloc, North America, and Oceania.

tude than that of the Cross-sectional results. As mentioned earlier, this heightened sensitivity is due to the more steeply shaped Experimental climate-response functions.

In order to shed more light on these results, we compare the GCM results to the impacts from a uniform climate change. We examine the impacts predicted by GIM using two uniform climate predictions: the area and population-weighted average temperature and precipitation change. The results are displayed in table 7. Even though uniformity implies the same change in temperature and precipitation in every country, the impacts vary widely. Countries that begin cool benefit whereas countries that begin warm are harmed. Comparing the uniform results to the impacts generated by the GCMs reveals significant differences. The average uniform scenarios predict large damages in low-latitude countries in Africa, Asia, and Latin America, and smaller benefits in high-latitude countries. The uniform climate changes overestimate global damages. The population-weighted results are better than the area-weighted estimates, but they suffer from the same problems. The uniform scenarios miss the important variation in temperature across latitudes.

This paper aggregates market effects across continents without making any adjustments for the incomes of the impacted countries. Some authors have argued that such adjustments should be made [5]. Unfortunately, the world has yet to agree on a social-welfare function that could generate such weights. Further, one would also have to weigh costs. As costs become more evenly distributed across countries, the importance of such weights diminishes [1]. Figures 1 and 2 both present impacts as a fraction of GDP. The results indicate that impacts will be small relative to GDP. Because the low-income countries tend to be clustered in the low latitudes, the maps also indicate that any weighting scheme that placed higher weights on low-income countries would tend to emphasize the damages in the more tropical countries relative to the benefits in the more temperate countries. Thus, the more weight one gave to low-income countries, the more the resulting index would lean towards damages.

4. Conclusion

This paper combines COSMIC, a climate-projection tool, and GIM, an impact-projection tool, to examine the country-specific market impacts predicted by 14 GCMs for 2100. Although there is considerable uncertainty about the exact magnitude of country-specific impacts, there are a number of insights from this research. First, the modest climate-change scenarios expected by 2100 are likely to have only a small effect on the world economy. The market impacts predicted in this analysis do not exceed 0.1% of global GDP and are likely to be smaller. Second, the market impacts will vary from country to country across the globe. High-latitude countries are expected to gain and low-latitude countries are expected to be harmed by warming. Third, although the overall effects of warming and carbon fertilization on the globe in 2100 are near zero, the marginal effect of higher temperature is expected to be harmful. Temperature changes beyond 2 °C are expected to reduce benefits and increase damages. Fourth, the GCMs predict greater warming near the poles and less warming near the equator relative to a uniform climate change scenario. These consistent deviations reduce damages (increase benefits) relative to a uniform climate change and should be taken into account. This research is intended to illustrate the power of COSMIC and GIM as forecasting tools. The research is also intended to reveal weaknesses or problems with these forecasts. For example, the current use of countrywide estimates of climate change is problematic for large countries because climates vary sufficiently within national borders that more localized estimates would be preferable. Another weakness in these forecasts is the reliance on annual temperature changes. Future models should attempt to model seasonal changes. A third prominent weakness involves the reliance on United States evidence to calibrate the responses to climate change. Clearly it would be preferable to have estimates of regional responses to climate change from around the world. Finally, in many sectors, it would be attractive to get more detailed information about each country. For example, there is no soil data in the current agriculture or forestry models, little information about space heating and cooling in the energy model, and little data about runoff in the water models. Prudent policy-makers should understand that the country-specific estimates of impacts are consequently preliminary and are likely to change as the models become more sophisticated.

Finally, we have measured only market effects from predicted climate changes. Preliminary research indicates that climate change is also likely to impact the quality of life. Effects on ecosystems, health, and aesthetics have not been taken into account in this analysis. Impacts from changes in extreme events or catastrophes should also be measured. As research in these areas develops, the model can be revised to include these more complete measures of impacts.

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