Climate Change Impacts and Ambiguity *

PRELIMINARY DRAFT - PLEASE DO NOT CITE

Stergios Athanassoglou, Emanuele Massetti †

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Abstract

In this paper we introduce a theoretical framework to establish a relationship between climate change impacts and global greenhouse gas (GHG) concentrations that takes into account the ambiguity - i.e. the structural uncertainty - that decision makers face when they have to assess future climate change impacts. We use US agriculture as a case study and estimate the sensitivity of agricultural land values and climate using a Ricardian model that distinguishes between cropland and non-cropland counties. We start by assessing climate change impacts for three SRES emission scenarios, in 2030, 2065 and 2100 for about 20 General Circulation Models (GCM). We show that *deterministic chaos* dominates the GCM scenarios and it discourages their use. For this reason we proceed by using simpler climate change models that generate probability density functions for climate sensitivity. We propose a simple decision-theoretic framework that takes into account ambiguity over climate sensitivity and helps decision makers visualize the full range of agricultural outcomes associated to a particular emissions trajectory. Nesting in a parametric fashion simple averaging and best/worst-case analysis, our model is intuitive, captures decision makers' ambiguity attitudes (i.e., tastes), and enables simple sensitivity analysis. We couple it to our Ricardian model of climate impacts to better discern the future effects of climate change on US agriculture.

Keywords: climate change impacts, ambiguity, aggregation

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†Athanassoglou: Fondazione Eni Enrico Mattei (FEEM) and Euro-Mediterranean Center for Climate Change (CMCC), athanassoglou@gmail.com. Massetti: Yale F&ES, FEEM and CMCC, emanuele.massetti@yale.edu

1 Introduction

Decision makers are facing the daunting task of implementing policies to reduce global warming and to adapt to a changing climate. This is one of the hardest policy challenges that our society faces, as the slow progress of international climate negotiations demonstrates. While it is clear that climate policy will not emerge as a result of a pure cost-benefit exercise, it is quite obvious that decision makers would value high the possibility to establish a relationship between global Greenhouse Gase (GHG) concentrations and local impacts. They could use this information to establish the preferred level of mitigation and to plan the necessary adaptations to the new climate.

In practice, no decision maker is, or ever will, be able to control global GHG concentrations. However, most decision makers will be able to vote and bargain for their preferred level of emissions on the basis of the national and local cost of reducing emissions and of coping with a new climate. This applies well to the US Senate, where senators have the interest to choose the amount of mitigation that maximizes the welfare of their voters. The same also applies to the European Union, in which member states could use veto power to oppose measures that harm their citizens.

Let us assume for the sake of simplicity that decision makers know with precision the cost of mitigation. Let us also assume that they trust a given impact model that relates local climate change and local physical or economic impacts. Even in this ideal world they would face a daunting question: how will future climate look like in my nation, state, city?

While climate models consistently show that higher concentrations of GHG in the atmosphere will cause global mean temperature to rise, they differ, often quite sharply, on the exact amount of additional warming that corresponds to a given concentrations pathway. Minimal differences in total cloud coverage affect greately climate sensitivity - i.e. the change of the global average temperature as a result of a doubling of CO2 concentrations. The IPCC Fourth Assessment Report (AR4) estimates that CS is likely to be in the range 2 to 4.5 C with a best estimate of about 3 C, and is very unlikely to be less than 1.5 C. Values substantially higher than 4.5°C cannot be excluded. Meinshausen et al. [30] collected estimates of climate sensitivity from a wider range of studies and show very disperse distribution, often characterized by "fat-tails".

Even more uncertain than global climate sensitivity are the local predictions of climate change. General circulation models (GCM) are progressively evolving into earth-system models to incorporate all the drivers of climate: vegetation, terrain, oceans, land ice, etc. Greater precision and greater geographical resolution however do not necessarily imply greater consensus (Knutti et al. [25], Knutti [23]). Consensus is also not increasing with new generations of models.

A careful analysis of the GCM runs used in the IPCC AR4 reveals that even if two models agree on the same global temperature response to higher concentrations of GHG they might predict two radically different geographic distributions of warming. Local rain patterns are even more difficult than local temperatures to predict. Models disagree on whether a given location is going to receive more or less rain than today.

We use a Ricardian model of US Agriculture to illustrate the full space of climate change impacts in 2030, 2065 and 2100 using all GCM runs available for the SRES scenarios B1, A1B and A2. In total we consider 150 climate change impact scenarios at county-level. Most studies on agriculture have instead considered at most three or four GCM scenarios. There are only two exceptions. Williams et al. [50] use the output of 16 GCM to study the impact of doubling CO2 concentrations on land values in the USA using a Ricardian model. Burke et al. [7], use the most recent set of SRES B1, A1B and A2 GCM scenarios to estimate the impact of climate change on the US corn-growing region.

With respect to Williams et al. [50] we consider a larger set of emission scenarios. We also use an updated version of the Ricardian model for the US which relies on panel data (Massetti and Mendelsohn. [29] henceforth MM) and separates impacts between cropland and non-cropland counties. With respect to Burke et al. [7] we do not focus only on grains in the Midwest but we cover 97 percent of US agricultural land. By focusing only on grains Burke et al. [7] greatly limit the adaptations that farmers can make to adjust to a new climate. Our model is able to generate both positive and negative outcomes while the model used in Burke et al. [7] generates only negative impacts because it excludes heat loving crops.

The abundance of scenarios provides a more complete set of information to policy makers but it is also a curse: the dispersion of climate change impact estimates is large and it is difficult to interpret. With non-linear response functions even relatively small differences across scenarios translate into large differences in the impact results. In some cases a model generates positive impacts when global concentrations are very high and negative impacts when they are low.

The question that the decision maker faces is then the following: what is the most sensible way of dealing with this large uncertainty?

A common thread running through much of decision making under uncertainty is a reliance on expected utility as a means of performing cost-benefit analysis and, more broadly, as a normative criterion. There are many compelling reasons behind its primacy: expected utility theory has solid theoretical underpinnings, going back to the work of von Neumann and Morgenstern [48] and Savage [38], is conceptually intuitive, and leads to tractable optimization problems. At its cornerstone is the belief that a model's probabilistic structure can be fully captured by a single Bayesian prior, which is then used in the decision-making process to adjudicate between uncertain tradeoffs.

In the case of climate-change economics, the attractive qualities of the expected utility paradigm come at a steep price. Unfortunately a clear-cut criterion to rank models according to accuracy does not exist and policy makers are left with little guidance (Knutti 2010 [23], Knutti et al. [25], Tebaldi and Knutti [45], Gleckler et al. [10]). Serious cognitive or informational constraints leave decisions makers uncertain about what odds apply to the payoff-relevant events. This creates obvious problems for the expected utility framework, and suggests that novel approaches may be called for.

The literature on decision making under uncertainty consistently uses the term "ambiguity" to denote a setting in which a decision maker is unable to posit precise probabilistic structure to physical and economic models. Instead, he perceives "uncertainty about probability, created by missing information that is relevant and could be known" (Frish and Baron, 1988). This framework derives from the concept of uncertainty as introduced by Knight [22] to represent a situation where a decision maker lacks adequate information to assign probabilities to events. Knight argued that this deeper kind of uncertainty is quite common in economic decision-making, and thus deserving of systematic study. Knightian uncertainty is contrasted to risk (measurable or probabilistic uncertainty) where probabilistic structure can be fully captured by a single Bayesian prior. There is considerable evidence that it may provide a more appropriate modeling framework for many applications in environmental economics, and especially climate change (Millner, Dietz, and Heal [33]). In this paper we apply models of decisions making under ambiguity to evaluate uncertain impacts of climate change.

The literature on the economics of climate change has steadily begun to embrace Knightian uncertainty. Millner et al. [33] apply the influential smooth ambiguity model of Klibanoff et al. [21] to determine the optimal level of global GHG concentrations. They use the DICE model (Nordhaus [36]) equipped with a global impact function which synthetically translates global mean temperature change into economic impacts. They show that as ambiguity aversion increases, emissions abatement increases and the "ambiguity premium" might be substantial. They focus their attention on the uncertainty that characterizes estimates of climate sensitivity, a measure of how much global temperature increases as concentrations of GHG in the atmosphere double. Therefore ambiguity definitely characterizes global decision making on the optimal level of GHG concentrations. Other studies along similar lines include Athanassoglou and Xepapadeas [5], Funke and Paetz [13], Gonzalez [18] and Lemoine and Traeger [27].

Even more compelling is the case for applying decision making theory under ambiguity when dealing with local impacts. Differences in climate change predictions and in local climate sensitivities enlarge enormously the range of possible impacts. Unfortunately we find that it is not possible to apply theories of decision making under ambiguity to impact estimates obtained using the IPCC AR4 scenarios.

In fact, we find that the IPCC AR4 scenarios are random draws from each own model pdf and are thus dominated by the *deterministic chaos* that governs climate. GCM models are very expensive to run and they cannot perform the Montecarlo-type of exercises that would allow building a pdf for each model. Some models might deliver scenarios that are well-centered around the mean, some might generate outliers (in both directions). This is an obstacle that we found to be insurmontable. We indeed find that the ”‘noise”’ in the climate change scenarios generated by each single GCM is large and has large consequences on impact estimates. It is therefore impossible to build the relationship between global concentrations and local climate change impacts that is of great interest for our decision maker.

For this reason we decide to use simpler and more tractable models that focus on global warming only instead of richer but less robust scenarios generated by GCMs. We know the pdf of climate sensitivity for all these models and we can therefore build our exercise on more solid grounds. We loose the richenss of the high resolution scenarios but we preserve the diversity of the local climate sensitivity over the US.

We use a simple 3-box climate module (MAGICC) that is used by most applied economists studying climate change (Nordhaus [36]) to link a wide range of emission pathways to global concentrations and we then calculate global temperature change by using the pdfs of climate sensitivities from all climate models surveyed by Meinshausen et al. [30]. We show how impacts change as a function of future emissions at US and regional level as a function of global emissions and of the level of ambiguity that a decision maker is willing to accept.

Decision-theoretic framework. We now briefly describe the mechanics of our decision-theoretic model. As an initial benchmark, our framework posits an equal-weight linear aggregation over diverging probability distributions of climate sensitivity. Subsequently, it considers enlargements of the set of possible aggregation schemes by parametrizing over their maximum distance, measured via the L_2 norm, with respect to the benchmark equal-weight aggregation. This distance is referred to as *aggregation ambiguity*. Next, our model computes the best-and worst-case expected outcomes of a given emissions trajectory, subject to the feasible set of distributions that is implied by assigned levels of aggregation ambiguity. Finally, we consider a convex combination of the best and worst-case expected outcomes as a reasonable way to model decision makers' preferences under aggregation ambiguity.

Our model nests in a parametric fashion simple averaging and best/worst-case analysis and allows for an expression of decision-makers' beliefs regarding, and attitude towards, the underlying uncertainty in climate model aggregation. Its simple structure allows for precise analytical insights, which have been studied in depth by Athanassoglou et al. [4].

We now discuss our model's relation to the existing literature. The maxmin/maxmax framework we use is a variation of the α-maxmin model that has been studied extensively in the decision-theoretic literature beginning with Hurwicz [19] and Arrow and Hurwicz [3]. Later contributions by Gilboa and Schmeidler [17], Ghirardato et al. [14], Chateaunauf et al. [8], and Eichenberger et al. [11] focused on axiomatic treatments of similar models in which a decision maker's actions are modeled by Savage acts [38], i.e. functions from a state space to a space of consequences. By contrast, our setting is considerably simpler as it does not introduce the notion of a state space, and its decision variables are real-valued vectors, not functions. An additional difference of our framework with respect to the above contributions is its specific consideration of aggregation ambiguity, which in turn controls the set of priors over which a decision-maker conducts his best- and worst-case analysis. No such variation in the set of priors is present in the aforementioned models as the amount and nature of ambiguity is a given model primitive. Finally, searching for the maximum and minimum payoff of an investment subject to an aggregation ambiguity b is reminiscent, at least in spirit, of the quantile-maximization model of Rostek [37].

We briefly comment on the connections between our approach and the smooth ambiguity model of Klibanoff et al. [21] that is commonly favored by applied/environmental economists interested in ambiguity (e.g., Gollier and Gierlinger [16], Millner et al. [33], Treich [46], Lemoine and Traeger [27]). On a fundamental level, the smooth ambiguity model achieves an elegant separation of beliefs and tastes regarding ambiguity, nesting in a smooth fashion the entire continuum between simple aggregation of the priors (ambiguity neutrality) to absolute focus on the worst-case (absolute ambiguity aversion). Comparative statics exercises involving the above are relatively easy to perform (at least in the static version of the model) and generate rich and insightful results. In this respect, our α-maxmin machinery is a little cruder and one can plausibly find fault with its consistent focus on best- and worst-case extremes. On the other hand, we believe there are advantages to our α-maxmin approach including: (a) the ability to model optimism, as well as pessimism, and; (b) a relatively straightforward interpretation of its ambiguity parameters. The latter could be important in practical policy making (i.e., "real world") settings, in which modeling assumptions need to be transparent and easy to understand. From a technical standpoint, a possible disadvantage of our model is that the value function describing preferences may in principle fail to be smooth but, as Athanassoglou et al. [4] argue, such concerns are either inapplicable or can be dealt with in a straightforward manner.

The rest of the paper is structured as follows. Section 2 introduces the impact model. We present and discuss estimates of the climate sensitivity of US agricultural land values. Section 3 presents the GCM scenarios and illustrates impacts on the US agricultural land values using the full set of models. Section 4 illustrates the decision-theoretic framework. A final Section presents concluding remarks.

2 The Ricardian model

2.1 Introduction

We use the United States (US) agriculture as a case study. This is an area in which research was intense in the past two decades. Early agro-economic models used crop-yield response functions to predict the impact of climate change (Adams [1], Kaiser et al. [20]; Adams et al. [2]). This first set of studies shows that moderate worming might be beneficial for the US agriculture. The agro-economic method contains limited adaptation possibilities and therefore overestimates negative impacts. However, the model includes the beneficial effect of CO2 fertilization. Mendelsohn et al. [32] proposed to use the cross-section variation of land values and climate to identify the outer envelope of the climate-land value relationship. Their approach is known as the Ricardian or hedonic method. Moderate climate change is beneficial for the US agriculture in the Ricardian model because the model assumes that farmers adapt to climate change. Farmers switch from cold-loving to heat-resistant crops and use techniques that make today profitable agriculture in areas that have climate similar to what they will experience in the future. The model implicitly assumes that large infrastructure projects, such as dams or canals for irrigation, will also be adapted to the new precipitations patterns, thus underestimating the cost and the difficulties of adaptation. However, the model also assumes that technology remains constant and underestimates potential for adaptation. New seed varieties that make crops more resistant to heat and to new rain patterns are a possible adaptation strategy that is not captured by the model.

Schlenker et al. [42] raised potential concerns on pooling irrigated and non-irrigated farmland together, and Schlenker et al. [43] suggested using degree days instead of average seasonal temperatures but confirmed the usefulness of estimating agriculture climate sensitivity exploiting the cross-section variation of climate and land values. The estimates of Schlenker and co-authors show that climate change has a negative impact on US agriculture. Deshenes and Greenstone [9] expressed concerns on the stability of Ricardian estimates due to unobserved heterogeneity. They suggest using the impact of random year-to-year variation in temperature and precipitation on agricultural profits to control for unobserved heterogeneity. As noted by Fisher et al. [12], the estimates of Deshenes and Greenstone are affected by data errors. Using the correct data, Fisher et al. show that climate change affects negatively the US agriculture. However, by using weather instead of climate as explanatory variable, Deshenes and Greenstone's method underestimates the adaptation potential. With a new specification of the Ricardian function and panel data Massetti and Mendelsohn [28] [29] show that Ricardian estimates are stable over the years and that it is possible to preserve climate as the explanatory variable.

In this study we rely on agriculture Census data from 1978, 1982, 1987, 1992, 1997, 2002. We pool of Census data together as in MM to estimate the relationship between climate and land values but contrarily to MM we estimate climate coefficients for cropland and non-cropland separately. We classify as cropland the agricultural land in counties in which cropland covers at least 30 percent of total land in farms. Cropland includes cropland harvested, cropland used only for pasture or grazing, cropland on which all crops failed or were abandoned, cropland in cultivated summer fallow, and cropland idle or used for cover crops or soil improvement but not harvested and not pastured or grazed (USDA [47]). Non-cropland has been determined as the difference between total land in farms and cropland. Non-cropland agricultural land is mainly used for pasture. According to the US Census, land classified as pasture encompasses grazable land that may be irrigated or dry land. In some areas, it can be a high quality pasture that could not be cropped without improvements. In other areas, it is barely able to be grazed and is only marginally better than wasteland (USDA [47]).

Table 1 contains descriptive statistics of key variables for cropland and non-cropland. Cropland has colder winters and warmer springs, summers and autumns. Non-cropland is drier in all seasons. The average value of farmland in counties with a high share of cropland is much higher than in counties classified as non-cropland. Irrigation is on average more common in cropland than in non-cropland counties. Cropland is concentrated around places with high density of population and higher income per capita, generally on lower elevation areas of the country. Ground water use is on average higher in non-cropland counties, while surface water use is higher in cropland counties. Figure 1 illustrates the distribution of cropland and non-cropland in the US. Counties in which non-cropland is a dominant share of farmland are mainly along the Rocky Mountains and in the South West. The Central Valley in California and the North West have the highest share of cropland in the West of the US. The highest share of cropland over total farmland is in the Mid-West, in the Northern Plains and along the Mississippi valley in the South East.

Greater precision in estimating present climate sensitivity comes at a cost: by assuming as fixed the distribution of agricultural land between cropland and non-cropland, we implicitly impose a constraint on the future possibilities of farmers to adapt to climate change. Several studies have shown that farmers in developing countries adapt to drier climate conditions and hotter climates by using mixed farms with crops and animals (Kurukulasuriya et al. [26], Seo [41], Seo and Mendelsohn [39] [40]). Also in the USA there is evidence that farmers might switch from cropland to pastureland as climate becomes hotter (Mu and McCarl [34]). Our estimates of climate change impacts are therefore negatively biased. If farmers are able to switch from cropland to other land uses they might limit the negative impact of climate change. In order to estimate the true impact of climate change one should estimate also the probability with which farmers choose the optimal distribution of land between cropland and non-cropland and see how this changes as climate changes. We leave this further step for a future analysis but we bear in mind the important implications of our assumption when interpreting results.

Soil data is aggregated at county level from the USDA NRI soil dataset. Geographic variables include, mean elevation, latitude, distance from metropolitan areas. Soil characteristics are salinity, flooding, wet index, K-factor (soil erodibility), lenght of slope, percentage of sand and clay, moisture level and permeability. Time dummies control for time trends common to all US agriculture. Socio-economic control variables include income per capita, density of population, density squared, an index of real estate values. (see the Data Appendix for further details). All socio-economic variables vary over time.

The value of land that we obtain from the Census includes the value of buildings. Land values from counties in which small farms with high valued residential properties might have an inflated value of farmland. In order to control for this problem we use the average size of farms in a county as a control variable. As in MM we use a log-model because it fits better US agricultural land values than a linear model.

[Table 1 about here]

[Figure 1 about here]

While MM estimate climate data at county-lvel using an interpolation method based on climate records at more than 7,700 weather stations, here we use 1961-1990 climate normals available on a 0.5'x0.5' high resolution grid from the Climatic Research Unit and the Tyndall Centre (New, Hulme, and Jones [35]). We downscale the GCM output to county-level by interpolating the four closest grid knots to each county's centroid, using weights inversely proportional to distance. We estimate a seasonal quadratic climate surface.[1] We have both theoretical and empirical justifica-

[1]Seasons are defined as usual in the literature: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), Autumn (September, October, November). Seasonal temperature is equal to the average over three months. Seasonal precipitation is equal to the sum of rainfall over the three months.

tions to differentiate climate among seasons. Farmers need rain and heat in well-defined periods. By using only one season it is not possible to distinguish periods in which warming is good from periods in which warming is harmful. This also applies to precipitations. The idea of using more sophisticated measures of climate like degree days (Schlenker et al. [43], Deschenes and Greenstone [9]) is appealing but it is in practice of small relevance because average daily temperatures in the US are mostly comprised between the lower and upper thresholds used to define degree days. Using growing season degree days is therefore practically equivalent to using average growing season mean daily temperature in the US.

The reduced-form Ricardian model that we estimate reads as follows:

$$v_{i,t} = X_{i,t}^{'}\boldsymbol{\beta} + Z_{i}^{'}\gamma + d1C_{i}^{'}\boldsymbol{\phi} + (1 - d1)\, C_{i}^{'}\boldsymbol{\mu} + u_{i,t}, \tag{1}$$

where $v_{i,t}$ is the logarithm of the value of land per hectare, $X_{i,t}$ is a vector of time-varying control variables, Z_i is a vector of time-invariant control variables, C_i is a vector of climate variables and water use, d_1 is a dummy variable that indicates whether a county's farmland is classified as cropland or not (primes denote vector transposes). We assume that the error term $u_{i,t}$ uncorrelated with climate variables. The impact of climate change in region r is measured as the change of land value per hectare under the new climate $V_i(C_1)$, with respect to land value per hectare under the 1961-1990 climate $V_i(C_0)$, aggregated over all farmland in a county and over all counties that belong to region r:

$$I_r = \sum_{i \in r} \left[V_i\left(C_1\right) - V_i\left(C_0\right)\right] F_i. \tag{2}$$

2.2 Results

Table 1 reports coefficients of temperature and precipitation variables, separated between cropland and non-cropland agricultural land. Table A1 in the Appendix reports the coefficients of all control variables. Most climate variables are highly significant, confirming that climate has a different impact on land values in different seasons.

Warming in winter and summer is harmful for all agricultural land. This is a finding common to many other Ricardian studies (Mendelsohn et al. [**?**], Mendelsohn and Dinar [31], Massetti and Mendelsohn [28] [29]). Cool winters are beneficial because they kill bugs and weeds. Warmer winters will be more harmful in counties that are already warmer than average. Cropland and non-cropland counties have a very similar response to warming in winters. Hot summers cause stress both for crops and animals. While the impact appears to be homogeneous among non-cropland counties, warming is going to be more harmful in cropland counties that are relatively warmer today.

Warm springs and autumns are beneficial because they extend the growing season. While cropland and non-cropland counties have the same response to warming in spring, warming in autumn is more beneficial for cropland. More precipitations are beneficial in all seasons but autumn. More rainfall is particularly beneficial for cropland in spring. Precipitations in summer are largely insignificant for cropland. This might seem counterintuitive but a careful analysis of Table 1 reveals that, on average, summer is the wettest season of the year for both cropland and non-cropland. However, non-cropland is on average drier than cropland and therefore we find that more rainfall is generally beneficial.

The allocation of land between cropland and non-cropland uses seems to be driven more by differences in rainfall than in temperatures. For this reason the response to a change in precipitations is more heterogeneous than the response to a change in temperature. A formal F-test reveals that the distinction between cropland and non-cropland is justified in particular for precipitations. The squared summer temperature coefficients and the linear autumn temperature coefficient are also significantly different (Table 2).

[Table 2 about here]

[Table 3 about here]

Before examining GCM climate change scenarios it is useful to test both seasonal and annual temperature and precipitation marginals using the average climate of the US and the average climate of ten representative macro-regions.[2]

There are several important messages that emerge from the analysis of Table 3 and Table 4, where all marginals are reported. First, seasonal temperature marginals are significant both for cropland and non-cropland. However, seasonal effects offset each other and generate non-significant annual marginals at US level and in most regions. Second, winter and spring temperature marginals have similar effect on both cropland and non-cropland. Summer marginals are instead more harmful for cropland, while autumn marginals are more beneficial for cropland than for non-cropland. Third, in both cropland and non-cropland there are significant regional differences: warming in California, Florida and in the South East is clearly harmful. The main reason is that they lack cool winters and extra warming causes larger negative effects during winter than in other regions. Fourth, we find strong significant seasonal and annual precipitation marginals. More rain is generally good in

[2] The regions abbreviations read as follows: CA, California; FL, Florida; MW, Midwest; NE, North East; NP, Northern Plains; NR, Northern Rockies; NW, North West; SE, South East; SP, Southern Plains; SR, Southern Rockies.

all seasons with the exception of autumn. A wet harvesting season is bad for crops. Fifth, more rainfall is generally good for both cropland and non-cropland but precipitations are particularly beneficial for non-cropland, because it is drier than cropland.

[Table 4 about here]

[Table 5 about here]

[Figure 2 about here]

3 Estimates of impacts using GCM scenarios

3.1 Analysis of climate change scenarios

We consider the B1, A1B and B1 GHG emission scenarios part of the Special Report on Emission Scenarios (SRES) (Nakicenovic et al. 2000). Figure 4 illustrates concentrations of CO2 in the atmosphere calculated from emission trajectories by the two carbon cycle models used by the GCMs: ISAM and BERN-CC. The concentrations were used by the GCMs to calculate radiative forcing and then global warming and climate change. While the A1B and A2 scenarios are two "business-as-usual" scenarios, the B1 scenario can be considered as a moderate stabilization scenario.

Through the IPCC Data distribution center we obtained 16 different GCM scenarios for the B1 SRES emission scenario, 20 for the A1B and 14 for the A2 scenario. For each scenario we consider the climatologies over three time periods: 2011-2030, 2046-2065 and 2081-2100. This makes a total of 150 observations. Table A8 in the Appendix lists acronyms and full names of all GCM used, the research centers to which they belong, the carbon cycle model they use, the scenarios available and grid resolution.

It is well-known that different GCMs may have a totally different view of local climate change patterns. We report the distribution of each GCM for seasonal temperatures and precipitations in 2100 in Tables A6 and A7 in the Appendix. For example, the CSMK3 model predicts that the median warming among all US counties in summer will be equal to 3.4C in 2100 with respect to 1961-1990. For the same emission scenario the GCM20 model predicts a median warming equal to 7.7C. The warmest US county during summer in 2100 will be 10.7C warmer than in 1961-1990 for the GCM20 model and 4.8C warmer for the CSMK3. In winter instead, the two models predicts a similar warming for the median county. The warmest county is instead much warmer in the CSMK3 than in the GCM20 scenario. The exact regional distribution of warming is also very different among models. The distribution of changes in precipitations is even more different because rainfall can either increase of decrease in future climate change scenarios. For the same region one model could predict a 30 percent increase of rainfall while another model could predict a 30 percent decline. We call this the "between models" uncertainty.

3.2 Impacts

Figure 3 illustrates the impact of climate change on total US farmland for the three SRES scenarios in 2030, 2065 and 2100. The figure reveals a large dispersion of estimates, especially at lower levels of concentrations. In the high emissions scenarios A1B and A2 most models predict a negative impact on the US agriculture in 2065 and 2100. The range is quite large and several models are able to generate positive impacts even in high warming scenarios. It is not possible to find patterns. A model that is fairly optimistic in one scenario might be pessimistic in another scenario. Some models generate positive impacts in 2065 and negative impacts in 2100.

Table 6 examines impacts at regional level. In 2100 the areas with the largest uncertainties are the North East, the Mid West, the Southern Rocky Mountains, the South East and the Southern Plains. The North West, Florida and the Northern Rockies are the regions in which there is greater agreement. Climate change is more harmful for the North West, the Northern Rockies, California and Florida. Surprisingly, the A2 scenario has higher warming but impacts in 2100 are equivalent to those in the A1B scenario.

[Figure 3 about here]

[Table 6 about here]

3.3 Uncertainty between and within models.

How should a decision maker interpret the wide range of results presented above? One possibility is to take the simple average of all impact estimates and consider this as the most likely outcome. An alternative would be to take the average of all GCM scenarios to estimate the climate change impact of the most likely future climate change scenario. However, both methods would be questionable because they assume that all GCMs have the same probability of generating the "true" future climate. Unfortunately, it is also not possible to build a weighted average which uses weights proportional to the accuracy with which each model describes future climate. Unfortunately a clear-cut criterion to rank models does not exist, mainly because the "true" future climate is not known. Models that replicate well past climate do not necessarily predict well future climate. It is then not correct to diregard scenarios which are at the extreme of the sample that we observe. They might have the same probability of being close to the "true" future climate than models that are at the center of the distribution.

Most importantly, averaging across GCM (or across estimates of impacts) is not a truly meaningful exercise because GCMs are not independent (Knutti et al. [24]). Some models were built using components of other models. Other models share the same sub-modules and other models were developed in the same research center (see table A8 in the Appendix). The mean of the sample of scenarios is not necessarily the mean of the distribution of future climate change.

Focusing only on the best/worst case would rarely deliver a meaningful meassage to the decision maker. For example, figure 3 shows that, in all years and in all scenarios, there is at least one model for which climate change is going to be very beneficial for the US agriculture and one model for which climate change is going to be highly harmful. The decision maker would be disoriented. Regional models are in large part coupled to global models and would not offer a valid alternative to GCMs (Knutti et al. [24]).

Expected utility theory is clearly of little guidance when it comes to assess future climate change impacts. It is however possible to aggregate the available information by treating explicitly the ambiguity that a decision maker has on the distribution of future climate change scenarios. The literature on decision-making under conditions of ambiguity has produced several methods to deal with this "deep" uncertainty on future climate change. Ideally, the decision maker would apply those methods to the impact estimates developed above. More precisily, she would like to pool all the combinations between GHG concentratoins and local impacts to study optimal climate mitigation and adaptation policies. Unfortunately, we find that both exercises would be not meaningful because the GCM scenarios are dominated by noise within each GCM.

Figure 2 shows that CO2 concentrations - CO2 is the most important among all GHG - are virtually the same for the three scenarios until 2020 and until 2050 for the A1B and the A2 scenarios. Differences between the scenarios are minimal. The difference between the A2 and the A1B scenarios from 2020 to 2050 is of at most 1.5 ppm. The two scenarios diverge only in 2060, when the A2 has 8 ppm more than the A1B scenario. One should bear in mind that concentrations raise from 325 in 1970 to 856 ppm in 2100 in the A2 scenario. We would then expect that the same GCM would generate climate change scenarios which are very similar for the years in which concentrations are virtually identical. We do not find evidence of this result: climate change scenarios generated by the same model, for different SRES scenarios, are very different in years in which they use almost identical concentration pathways.

Figure 3 provides a striking example for the HADCM3 model of the UK Metereological Center. Tables A2-A5 in the Appendix reveal that this holds for all models, for both temperatures and precipitations. If we take as example temperature change in 2030 (2011-2030 average), we see that the differences in warming across the three scenarios are remarkable. While in the B1 and A2 scenarios January temperature in the East, and especially in the Mid-West, is much lower than in

1961-1990, in the A1B scenario the East becomes up to 3.5C warmer. The range of temperature change that we find for the same region is about 4C, for a virtually identical level of concentrations. In case of precipitations we often see that in one scenario, for the same region, rainfall increases while in another rainfall decreases. The same applies to 2065, for the HADCM3 A1B and A2 scenarios (see Tables A2-A5).

What can explain this seemingly odd result? What are the implications for estimating climate change impacts with GCM scenarios?

Climate change models incorporate deterministic chaotic dynamics that generate very different future trajectories of climate starting from very minor differences in the initial conditions. The large discrepancies among the scenarios do not mean that the climate models are poorly conceived. Rather, it means that chaos is a key determinant of weather and climate.[3] It is however surprising that weather anomalies do not converge to the same mean even if we consider a twenty-year period. One possible answer is that the signal in 2030 is still too weak with respect to the background noise. However, we find large differences also in 2065, when the signal is much stronger. The most plausible explanation is that the chaotic dynamic is very strong and has been so far underestimated or simply neglected by the literature on climate change impacts. We refer to this as the "within models" uncertainty.

Figure 5 shows how the "within models" uncertainty affects estimates of impacts. In many cases very similar levels of concentrations generate very different impacts. The noise in the climate predictions is still very strong in 2065, when concentrations increase by 50 percent with respect to 2010. For this reason we conclude that great caution should be used when interpreting the impact estimates presented above. It is also not possible to pool different SRES scenario and obtain a general relationship between global GHG concentrations and climate change impacts.

If we had many runs of the same SRES scenario from the same model it would be possible to estimate a probability density function (pdf) of climate change and then examine the expected value and the variance of the distribution. Unfortunately generating a scenario requires weeks - if not months - using large and costly super-computers. For this reason we have only one run available for each SRES scenario. We basically have only one random draw from the pdf of each GCM. The whole modeling inter-comparison exercise for the IPCC AR4 seems thus dominated by noise and we believe it cannot be the foundation of robust decision making.

For this reason we explore an alternative approach. We consider simpler climate models whose primary scope is to study how the global mean temperature changes in response to the accumulation of GHG in the atmosphere. These models require much less computational power and can be run

[3]An excellent introduction to climate change models for economists is Auffhammer et al. (2011).

many times in order to generate pdfs. They provide a less detailed but more solid foundation for interpreting impacts of climate change.

[Figure 4 about here]

[Figure 5 about here]

3.4 Estimates of impacts using global mean temperature scenarios

We consider the set of climate models examined by Meinshausen et al. [30]. For each model we know the pdf of the climate sensitivity (CS) - i.e. the increase of global mean temperature as a consequence of the doubling of CO2 concentrations with respect to the pre-industrial level. The IPCC Fourth Assessment Report (AR4) estimates that CS is likely to be in the range 2 to 4.5 C with a best estimate of about 3°C, and is very unlikely to be less than 1.5°C. However, climate models do not rule out the possibility that CS might be very high, with possibly alarming consequences (see Figure 6). The possibility of having fat right tails of the distributions supports the adoption of a precautionary approach (Weitzman [49]).

Unfortunately the models do not provide information on precipitations. We assume that global precipitations increase linearly by 3.4 percent for each degree Celsius of temperature increase (referenceee).

We calculate the impact of a uniform warming scenario on US cropland and non-cropland counties and we aggregate the change of land values at regional and national level (Figure 7). We consider warming from 0.1 to 10C, with decimal degrees steps.

Results show that uniform warming and a moderate increase in precipitations always lead to a contraction of US agricultural land values. However, the impact is moderate: with a 4C warming scenario total land values decline by 5 percent. As mentioned above, it is important to stress the fact that we are not considering the possibility that farmers switch from cropland to non-cropland as an adaptation to climate change. Regional impacts differ substantially. For the South-East, the Southern Plaines the North-West, California and Florida warming is always harmful. Moderate warming is beneficial in cooler regions like the North-East, the Mid-West and the Northern Plains. The Southern Rockies are an area with abundant pastureland. The impact of warming is always beneficial. It is possible that future temperatures in the Southern Rockies, California and Florida increase well beyond what we record today in the US. Extrapolating out-of-sample future climate change impacts might not be legitimate in case of extremely high warming. Out-of-sample issues might also explain why California, Florida and the Northern Rockies have a u-shaped response function with a minimum close to 10C. Further draft of this paper will examine the impact of additional rainfall separately from the impact of temperatures. It is also possible to study separate response functions for cropland and non-cropland.

The scenarios that we use are very rough representations of future climate patterns in the US. They are built on the unrealistic assumption that warming will be homogeneous and that all counties will benefit from moderate additional precipitations. Unfortunately, scenarios generated by GCMs do not allow any meaningful relatioship between global concentrations and local climate changes. For this reason in the next section we base our decision-theoretic model on the uniform climate change scenarios.

[Figure 6 about here]

[Figure 7 about here]

4 Ambiguity

4.1 Model Description

Consider a set $\mathcal{M}$ of climate models indexed by $m = 1, 2, ..., M$. Time is discrete and indexed by $t = 1, 2, ...t_n$ and a dynamic path of radiative forcing is denoted by a vector $\mathbf{f} = \{f_1, f_2, ..., f_{t_n}\}$.[4] Climate sensitivity is denoted by a parameter s that lies in a domain S. In line with Meinshausen et al. [30], we take $S = [1, 10]$.[5] Given a path of radiative forcing $\mathbf{f}$, an initial temperature increase of $T(0)$ (as well as $T_{LO}(0)$, where LO stands for lower ocean) and a value of climate sensitivity s, we may use a simple 3-box climate module (see Nordhaus [36]) to deduce a dynamic path of temperature increase $\boldsymbol{T}(\boldsymbol{f}, s) = \{T_1(\boldsymbol{f_1}, s), T_2(\boldsymbol{f_2}, s), ..., T_{t_m}(\boldsymbol{f_{t_k}}, s)\}$ (here $\boldsymbol{f_k}$ denotes the restriction of vector $\boldsymbol{f}$ to its first k-coordinates).

Each climate model m is characterized by its individual pdf of climate sensitivity s denoted by

$$\pi_m(s). \tag{3}$$

As Figure 6 suggests (Meinshausen et al. [30]), pdfs π_m will vary significantly across climate models and it is difficult to rule out extreme values of climate sensitivity. The question thus naturally arises: How do we make sense of this considerable divergence? In the absence of data that could lend greater credibility to one expert over another and form the basis of a Bayesian

[4] Vectors are denoted in bold. In this preliminary version of the paper we simplify and consider radiative forcing trajectories, not emissions, as our decision variable. For an explanation of radiative forcing and its connection to emissions and concentrations of CO_2 please see Nordhaus [36].

[5] We disregard values of s between .1 and 1 as they lead to nonsensical temperature dynamics when applied to the simple 3-box climate module we employ (Nordhaus [36]). Since such small values of s occur with negligible probability, this truncation results in no significant loss of generality.

analysis, one straightforward way would be to simply aggregate over all pdfs π_m so that we obtain an "aggregate" joint pdf $\bar{\pi}$, where

$$\bar{\pi}(s) = \sum_{m=1}^{M} \frac{1}{N} \pi_m(s). \tag{4}$$

This approach inherently assumes that each and every climate model is equally likely to represent reality and makes use of simple linear aggregation. While this is standard practice in many economic contexts, a great deal of valuable information may be lost in such an averaging-out process, especially when inter-model differences are significant.

We thus move beyond simple averaging. In our framework each pdf π_m is weighted by the decision maker through a second-order probability p_m. The set of admissible second-order distributions $\mathbf{p}$ depends on the amount of ambiguity the decision maker is willing to take into account when aggregating across climate models, and in particular on how "far" he is prepared to stray from equal-weight aggregation. Specifically, we consider the set of second-order distributions $\mathrm{P}(b)$ over the set of M climate models, parametrized by $b \in \left[0, \frac{N-1}{N}\right]$ where

$$\mathrm{P}(b) = \left\{ \mathbf{p} \in \Re^M : \;\; \mathbf{p} \geq \mathbf{0}, \;\; \sum_{m=1}^{M} p_n = 1, \;\; \sum_{m=1}^{M} \left(p_m - \frac{1}{M} \right)^2 \leq b \right\}. \tag{5}$$

Here, the set $\mathrm{P}(b)$ captures the uncertainty of the decision-maker's aggregation protocol. Thus, we refer to parameter b as *aggregation ambiguity*. Letting $\boldsymbol{e_M}$ denote a unit vector of dimension M, we see that distributions $\mathbf{p}$ belonging to $\mathrm{P}(b)$ satisfy $||\mathbf{p} - \frac{\boldsymbol{e_M}}{M}||_2 \leq \sqrt{b}$, where $||\cdot||_2$ denotes the L_2-norm. Setting $b = 0$ implies complete certainty and adoption of the equal-weight singleton, while $b = \frac{M-1}{M}$ complete ambiguity over the set of all possible second-order distributions.[6]

We briefly provide a potential interpretation of an ambiguity level b in our model. Consider the benchmark equal-weight distribution $\frac{1}{M}\, \boldsymbol{e_M}$. Now take a set of climate models $\widehat{\mathcal{M}}$ of cardinality $\widehat{M}$ and begin increasing the collective second-order probability attached to their pdfs. The convex structure of the feasible set $\mathrm{P}(b)$ enables us to provide a tight upper bound on the maximum second-order probability $p(b, \widehat{M}; M)$ that can be placed on this set of models, as a function of b and $\widehat{M}$:

$$p(b, \widehat{M}; M) = \max_{\mathbf{p} \in \mathrm{P}(b)} \; \max_{\left\{ \widehat{\mathcal{M}} \subseteq \mathcal{M} : \; |\widehat{\mathcal{M}}| = \widehat{M} \right\}} \sum_{m \in \widehat{\mathcal{M}}} p_m = \min \left\{ \frac{\widehat{M}}{M} + \widehat{M} \sqrt{\frac{M - \widehat{M}}{\widehat{M} M} b}, \; 1 \right\}. \tag{6}$$

[6] The latter statement holds in light of the fact that values of $b > \frac{M-1}{M}$ cannot enlarge the feasible set. This is because the maximizers of $\sum_{m=1}^{M} \left(p_m - \frac{1}{M} \right)^2$ over the set of probability vectors concentrate all probability mass on one model, leading to an aggregation ambiguity of $\left(1 - \frac{1}{M}\right)^2 + (M-1) \cdot \left(\frac{1}{M}\right)^2 = \frac{M-1}{M}$.

Weighting climate model pdfs (3) under all aggregation schemes belonging in $\mathrm{P}(b)$ induces the following set of priors

$$\Pi(b) = \left\{ \sum_{m=1}^{M} p_m(b)\pi_m(\cdot) : \quad \mathbf{p} \in \mathrm{P}(b) \right\} \tag{7}$$

that characterize climate sensitivity given a level of aggregation ambiguity b. Thus, holding all else fixed, an increase in b implies an expansion of the set of priors a decision maker is willing to consider.

The analysis in preceding sections yielded a vector-valued function $\boldsymbol{I}(T)$ that maps (uniform) temperature increase to agricultural impacts across all US regions. Incorporating the dependence of temperature on radiative forcing $\boldsymbol{f}$ and climate sensitivity s, we may rewrite the above as the vector-valued function (across time and space)

$$\boldsymbol{I}(\boldsymbol{T}(\boldsymbol{f}, s)).$$

Each climate model m will lead to a different estimate of expected impacts, i.e.,

$$\boldsymbol{EI_m}(\boldsymbol{f}) = \int_S \boldsymbol{I}(\boldsymbol{T}(\boldsymbol{f}, s))\mathrm{d}\pi_m(s). \tag{8}$$

Now, given a forcing trajectory $\boldsymbol{f}$, impact function I, and the set of second-order distributions $\mathrm{P}(b)$ introduced in (5), we can calculate the best- and worst-case expected impacts associated with $\boldsymbol{f}$, given aggregation ambiguity b. This provides a measure of the spread between the worst and best-case impacts, given a "willingness" to stray from the benchmark equal-weight distribution that is constrained by b. More formally, we consider the vector-valued functions (across time and space):

$$\begin{aligned} \boldsymbol{V_{max}}(\boldsymbol{f}|b) &= \max_{\pi \in \Pi(b)} \int_S \boldsymbol{I}(\boldsymbol{T}(\boldsymbol{f}, s))\mathrm{d}\pi(s) = \max_{\mathbf{p} \in \mathrm{P}(b)} \sum_{m=1}^{M} p_m \boldsymbol{EI_m}(\boldsymbol{f}) && (9) \\ \boldsymbol{V_{min}}(\boldsymbol{f}|b) &= \min_{\pi \in \Pi(b)} \int_S \boldsymbol{I}(\boldsymbol{T}(\boldsymbol{f}, s))\mathrm{d}\pi(s) = \min_{\mathbf{p} \in \mathrm{P}(b)} \sum_{m=1}^{M} p_m \boldsymbol{EI_m}(\boldsymbol{f}). && (10) \end{aligned}$$

The second equality in Eqs. (9) and (10) is valid by the linearity of the expectation operator. Plotting functions (9) and (10) over $b \in [0, (M-1)/M]$ gives decision makers a comprehensive picture of the impacts of a forcing trajectory $\boldsymbol{f}$.

The functions (9)-(10) fix a level of aggregation ambiguity b and subsequently focus on the best and worst cases. As such, they capture extreme attitudes towards uncertainty in aggregation. To express more nuanced decision-maker preferences we consider the following vector-valued value function

$$\boldsymbol{V}(\boldsymbol{f}|b, \alpha) = \alpha \cdot \boldsymbol{V_{min}}(\boldsymbol{f}|b) + (1-\alpha) \cdot \boldsymbol{V_{max}}(\boldsymbol{f}|b) \quad \alpha \in [0, 1], \tag{11}$$

representing a convex combination of the worst- and best-cases. The parameter α above captures the decision maker's *ambiguity attitude*. It measures his degree of pessimism given aggregation ambiguity b: the greater (smaller) α is, the more (less) weight is placed on the worst-case scenario.

4.2 Relation to the literature

Our model nests in a parametric fashion simple averaging and best/worst-case analysis and allows for an expression of decision-makers' beliefs regarding, and attitude towards, the underlying uncertainty in model aggregation. The maxmin/maxmax framework we use is a variation of the α-maxmin model that has been studied extensively in the decision-theoretic literature beginning with Hurwicz [19] and Arrow and Hurwicz [3]. Later contributions by Gilboa and Schmeidler [17], Ghirardato et al. [14], Chateaunauf et al. [8], and Eichenberger et al. [11] focused on axiomatic treatments of similar models in which a decision maker's actions are modeled by Savage acts [38], i.e. functions from a state space to a space of consequences. By contrast, our setting is considerably simpler as it does not introduce the notion of a state space, and its decision variables are real-valued vectors, not functions. An additional difference of our framework with respect to the above contributions is its specific consideration of aggregation ambiguity, which in turn controls the set of priors over which a decision-maker conducts his best- and worst-case analysis. No such variation in the set of priors is present in the aforementioned models as the amount and nature of ambiguity is a given model primitive. Finally, searching for the maximum and minimum payoff of an investment subject to an aggregation ambiguity b is reminiscent, at least in spirit, of the quantile-maximization model of Rostek [37].

We briefly comment on the connections between our approach and the smooth ambiguity model of Klibanoff et al. [21] that is commonly favored by applied economists interested in ambiguity (e.g., Gollier and Gierlinger [16], Millner et al. [33], Treich [46], Lemoine and Traeger [27]). On a fundamental level, the smooth ambiguity model achieves an elegant separation of beliefs and tastes regarding ambiguity, nesting in a smooth fashion the entire continuum between simple aggregation of the prior π's (ambiguity neutrality) to absolute focus on the worst-case (absolute ambiguity aversion). Comparative statics exercises involving the above are relatively easy to perform (at least in the static version of the model) and generate rich and insightful results. In this respect, our α-maxmin machinery is a little cruder and one can plausibly find fault with its consistent focus on best- and worst-case extremes. On the other hand, we believe there are advantages to our α-maxmin approach including: (a) the ability to model optimism, as well as pessimism, and; (b) a relatively straightforward interpretation of ambiguity parameters b and α. The latter could be important in practical policy making (i.e., "real world") settings, in which modeling assumptions need to be transparent and easy to understand. From a technical standpoint, a possible disadvantage of our model is that the value function (11) may in principle fail to be smooth, but as Athanassoglou et al. [4] argue, such concerns are either inapplicable or can be dealt with in a straightforward manner.

4.3 Narrowing our focus

Eq. (11) can be applied to any forcing trajectory $\boldsymbol{f}$. Indeed, given values for α and b, we could in theory search for an optimal $\boldsymbol{f}$ by using appropriately-defined first-order conditions.[7] However, in this preliminary version of the paper we reduce the problem's complexity and focus on trajectories satisfying:

$$\boldsymbol{f}(x) = x\ \boldsymbol{f^N} + (1-x)\ \boldsymbol{f^S} \quad x \in [0,1], \tag{12}$$

where $\boldsymbol{f^N}$ represents the forcing trajectory of the Business as Usual (BAU) scenario of William Nordhaus' 2010 DICE model [36], while $\boldsymbol{f^S}$ the most aggressive mitigation trajectory (corresponding to an estimated stabilization of GHG concentrations at 450ppm) of the Stern Review [44]. We focus on convex combinations of these two forcing paths because they represent two polar, and iconic, opposites that have so far framed the economics debate over optimal mitigation trajectories. In our view, convex combinations of these two extremes span, at least reasonably well, the space of forcing trajectories that policy makers are called to choose from.

In order to better visualize the effect of x and b on agricultural impacts, we fix ambiguity attitude at $\alpha \in \{0, 1\}$ and plot best and worst-case expected impacts (9)-(10) as a function of x and b. Our main objective is to gain qualitative insight by comparing forcing trajectories satisfying (12). For this reason, we do not pursue optimization over a continuous forcing domain (we plan to do this in future work). As the purpose of this preliminary exercise is to provide a conceptual illustration of our method and the range of agricultural impacts that may come to pass as a result of global warming, this simplification is legitimate.

In this preliminary version of the paper we concentrate on agricultural impacts in year 2115, i.e., roughly 100 years from now. This allows for enough time to observe noticeable effects on temperature due to climate change. For reasons that will become clear shortly, we draw attention to three regions: (a) the whole US, (b) the Northeast (NE), and (c) the Southeast (SE). Now, let us revisit on Figure 4 that was introduced in the previous section. US-wide impacts are shown to be decreasing in temperature, reaching a minimum of about -17% for a temperature increase of 10 degrees Celsius. However, as mentioned earlier, impacts will not be uniform across regions

[7] Results in Athanassoglou et al. [4] provide guidance on how to perform such an optimization exercise.

and we subsequently focus on the NE and SE regions precisely because they nicely illustrate this considerable geographic heterogeneity. As Figure 4 suggests, the NE stands to gain from a climate change of up to 7.5 degrees; moreover, for temperature increases between 0 and 4 degrees, NE impacts will actually be *increasing* in temperature. By contrast, the SE suffers consistently negative impacts that are strongly decreasing in temperature, reaching a minimum of about -50% for 10 degrees Celsius. Such spatial differences could in principle lead to interesting political-economy issues in the formulation of US-wide climate policy.

Figure 8 plots $\boldsymbol{V_{max}}\left(\boldsymbol{f}(x)|b^2\right)$ and $\boldsymbol{V_{min}}\left(\boldsymbol{f}(x)|b^2\right)$ over $b \in \left[0, \sqrt{\frac{19}{20}}\right] \approx [0, .98]$ and $x \in [0,1]$, restricted to year 2115 and the US, NE, and SE.[8] The parametrization b^2 is adopted since it allows us to (a) dampen the curvature of the original functions and (b) interpret the parameter b as a bound on the Euclidean distance of admissible aggregation schemes with respect to the benchmark equal-weight aggregation.

We focus first on the entire US. The first panel of Figure 8 shows that impacts will be consistently, if moderately, negative for all x and b. They are strictly decreasing in x which suggests that higher emissions will always be damaging to agriculture. At the absolute best case (corresponding to $x = 0$ and $b = .98$) imapcts will be just slightly below 0, while at the absolute worst case ($x = 1$, $b = .98$) they will be around -8%. Moving now to the NE, the picture is considerably different. Here, impacts are uniformly slightly positive, implying that global warming will have a mildly beneficial effect on agriculture ranging between 2 and 4%. Moreover, the relationship between x and impacts is no longer monotonic. Instead, we see that for all $b \in [0, .98]$, best- and worst-case impacts will have a concave inverted-U shape, suggesting that middle-range values of x, and therefore abatement, will be "optimal". This picture is in strong contrast to results for the SE. There, impacts will be uniformly and solidly negative, ranging from -5 to -15% and higher values of x will always result in greater agricultural damages.

With the decision-theoretic framework that we have built in this section a decision maker has a tool to perform a cost-benefit assessment of mitigation policy when climate change impacts are ambiguous. We do not enter into the details of the cost-benefit problem because it is not the aim of this paper to find solve the optimization problem. We have shown that it is possible to connect global emission pathways, global warming and local impacts in a coherent decision-theroretic framework. Further research in this area seems promising and much needed to guide complex decisions in an optimal way.

[8] All simulations are performed in Mathematica.

5 Conclusions

With this paper we aim at providing guidance to decision makers that are trying to answer the following question: what is the preferred level of global GHG emissions for my constituency? These decision makers might not be willing to apply cost-benefit analysis literally because climate change is an extremely complex problem in which values, ethical considerations, inter-generational and intra-generational distribution issues play a major role. They would however give a high value to a decision method that allows them to resolve the large uncertainty that they face when they examine the large array of future climate change scenarios.

In order to provide a measure of the uncertainty that decision makers must face we use US agriculture as a case study. We estimate a Ricardian model that distinguishes between cropland and non-cropland counties and we estimate climate change impacts on all US agricultural land in our panel (97 percent of total) using 150 climate change scenarios produced by about 20 General Circulation Models (GCMs) for the IPCC Fourth Assessment Report (AR4).

We find that estimates of climate change impacts on US agriculture change significantly from one GCM to another. In some cases while one model predicts high positive gains another predicts large negative losses, for the same level of GHG concentrations. Unfortunately, we also discover that the deterministic chaos that governs climate generates a large amount of noise that make it almost impossible to use the scenarios in a meaningful way.

For this reason we abandon the richness of detail of GCM scenarios in favor of simpler global warming scenarios with known probability distribution functions of global climate sensitivity. In particular, we adopt a simple three-box climate module used by most economists studying climate change [36] and combine it with the divergent probabilistic estimates of climate sensitivity summarized in Meinshausen et a. [30].

We use this simpler setting to propose a model of decision-making under ambiguity. Our model nests in a parametric fashion simple averaging and best/worst-case analysis and allows for an expression of decision-makers' beliefs regarding, and attitude towards, the underlying uncertainty in model aggregation. We see the primary advantages of our approach as being those of intuitiveness and practicality. Admitting simple mathematical structure and easy interpretation, our model provides a straightforward way of introducing ambiguity to the climate-change debate. It is our hope that policy makers and the concerned community at large may find our approach useful in visualizing the set of possible alternatives and making informed decisions given their particular beliefs about, and attitude towards, ambiguous expert opinion.

We go on to illustrate our framework with data obtained from the previously-derived Ricardian model. In this preliminary version of the paper we concentrate on agricultural impacts in year 2115, i.e., roughly 100 years from now and draw attention to three regions: (a) the whole US, (b) the Northeast (NE), and (c) the Southeast (SE). US-wide impacts are shown to be consistently mildly negative and decreasing in temperature. However, as mentioned earlier, these effects will not be uniform across regions and we subsequently focus on the NE and SE regions precisely because they nicely illustrate this considerable geographic heterogeneity. Indeed, in the NE impacts are uniformly slightly positive, implying that global warming will have a small beneficial effect on agriculture. Moreover, the relationship between emissions and impacts is no longer monotonic. Instead, we observe a concave inverted-U shape, suggesting that middle-range values of abatement will be "optimal". This picture is in strong contrast to results for the SE. There, impacts will be uniformly and solidly negative, and higher emissions will always result in greater agricultural damages. Such spatial differences could in principle lead to interesting political-economy issues in the formulation of US-wide climate policy.

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6 Data Appendix

We use a balanced panel with observations for 2,914 counties in the contiguous 48 States over the years 1978, 1982, 1987, 1992, 1997 and 2002. Units of measurement are in the metric system; economic variables have all been converted to constant 2000 US using the GDP deflator. If not otherwise stated, variables measure data of interest in years 1978, 1982, 1987, 1992, 1997 and 2002.

6.1 Time varying, county specific socio-economic variables

Farmland Value - Logarithm of Estimated Value of Land and Buildings, average per hectare of farmland ($/ha). Data source is the Agricultural Census. Farmland - Land in farms as in the Census of Agriculture from 1978 to 2002, hectares (ha). The Census of Agriculture defines "Land in farms" as agricultural land used for crops, pasture, or grazing. It also includes woodland and wasteland not actually under cultivation or used for pasture or grazing, provided it was part of the farm operator's total operation. Large areas of woodland or wasteland held for nonagricultural purposes were deleted from individual reports. Land in farms includes acres in the Conservation Reserve and Wetlands Reserve Programs. Land in farms is an operating unit concept and includes land owned and operated as well as land rented from others. Cropland - Total cropland. This category includes cropland harvested, cropland used only for pasture or grazing, cropland on which all crops failed or were abandoned, cropland in cultivated summer fallow, and cropland idle or used for cover crops or soil improvement but not harvested and not pastured or grazed (USDA 2009). Income - Per capita personal income ('000 $); Bureau of Economic Analysis, Regional Economic Accounts, table CA1-3. Density - Population per squared kilometre ('000/km2), Bureau of Economic Analysis, Regional Economic Accounts, table CA1-3. Greenhouses - Share of total crop sales from nursery, greenhouse and floriculture (Subsidies - Government payments per hectare of land ($/ha). Source: Census of Agriculture. Real Estate - Median value for all owner-occupied housing units ('000 $). Census of Population and Housing, 1980, 1990 and 2000. Values for panel years have been computed extrapolating linear trends from the three census years available.

6.2 Time invariant, county specific, climate variables

Climate Variables - Climate Variables (CRU CL 1.0 0.5 dataset) - A dataset of mean monthly surface climate over global land areas, excluding Antarctica. Interpolated from station data to 0.5 degree lat/lon for a range of variables. The data are described in New, Hulme, and Jones (1999). Available at: http://ipcc-ddc.cru.uea.ac.uk . We determine climate at the centroid of each county by interpolating the four closest grid knots, weighting by the inverse of distance. Climate Variables (CRU CL 1.0 0.5 dataset) - A dataset of mean monthly surface climate over global land areas, excluding Antarctica. Interpolated from station data to 0.5 degree lat/lon for a range of variables. The data are described in New, Hulme and Jones (1999). Available at: http://ipcc-ddc.cru.uea.ac.uk . We determine climate at the centroid of each county by interpolating the four closest grid knots, weighting by the inverse of distance.

6.3 Time invariant, county specific soil characteristics

Salinity - Percentage of agricultural land that has salinity-sodium problems. Flooding - Percentage of agricultural land occasionally or frequently prone to flooding. Wet Factor - Percentage of agricultural land that has very low drainage (Poor and Very Poor). K-factor - Average soil erodibility factor. It is the average soil loss in tons/hectare; is a measure of the susceptibility of soil particles to detachment and transport by rainfall and runoff. Slope Length - Average slope length factor, meters (m). Slope length is the distance from the point of origin of overland flow to the point where either the slope gradient decreases enough that deposition begins, or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel. For the NRI, length of slope is taken through the sample point (Source: USDA; http://www.nh.nrcs.usda.gov/technical/NRI/NRIglossary.html).

Sand - Percentage of agricultural land classified as sand or coarse-textured soils. Clay - Percentage of agricultural land that is classified as clay. Moisture Level - Minimum value for the range of available water capacity for the soil layer or horizon, expressed as centimeters. Permeability - The minimum value for the range in permeability rate for the soil layer or horizon, expressed as centimeters/hour.

6.4 Time invariant, county specific geographic variables

Latitude - Latitude of county's centroid in decimal degrees (DD). Elevation - Elevation of county's centroid in meters. Distance from Metropolitan Areas - Distance in kilometers between county's centroid and metropolitan areas with more than 200,000 inhabitants in 2000. Surface Water Withdrawal - Thousands of liters per hectare, per day, of surface fresh water for irrigation purposes. The 'Estimated Use of Water in the United States', published every five years by the United States Geological Survey (USGS), supplies data on water use at county level only starting from 1985. We divided the amount of water used at county level for years 1985, 1990, 1995, 2000 by the amount of farmland in that county in Census years 1987, 1992, 1997 and 2002, respectively, and we computed the time average of surface water use per hectare of land. We used this variable as a proxy for surface water availability, at county level, for all time observations of our panel.

List of Tables

	Cropland				Non-cropland			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Temperature (°C)								
winter	-0.7	6.5	-14.8	19.3	0.6	6.2	-13.6	18.8
spring	11.2	4.4	-0.5	23.7	10.5	5.2	-3.6	23.6
summer	22.9	3.0	10.4	32.0	21.6	4.1	8.4	30.8
autumn	12.3	4.4	1.5	25.2	11.5	5.1	-0.8	25.0
Precipitations (mm)								
winter	50	40	7	459	30	32	8	288
spring	78	30	4	199	43	21	5	152
summer	85	29	1	199	50	25	1	219
autumn	67	29	6	289	39	20	9	159
Value land ($ / ha)	3483	2442	554	79686	1214	1532	341	25544
Farmland ('000 ha)	192	164	0	1197	648	553	1	2569
Share of cropland (%)	65%	18%	30%	97%	12%	9%	0%	30%
Farmland irrigated (%)	6%	12%	0%	84%	4%	5%	0%	36%
Income ('000 $)	18.8	2.9	10.3	41.4	17.4	3.8	7.4	44.2
Pop. density (persons/sq km)	28	62	0	2140	8	38	0	1162
Average elevation (m)	437	375	1	2888	1212	625	1	3330
Surface water (t/ha/day)	0.7	1.6	0.0	16.1	0.3	0.8	0.0	10.8
Ground water (lts/ha/day)	0.8	3.1	0.0	44.6	1.1	2.3	0.0	24.1

Notes: County-level data weighted by the average land in farms over the six Census years. Average value over the Census years used for all time-varying variables.

Table 1. Descriptive statistics of climate and other major variables in cropland and non-cropland.

	Non-Cropland	Cropland		Non-Cropland	Cropland
Temp Winter (℃)	-0.192***	-0.241***	Prec Winter (cm)	0.00900***	0.00212***
	[0.0250]	[0.0111]		[0.00134]	[0.000695]
Temp Winter sq (℃)	-0.00505***	-0.00471***	Prec Winter sq (cm)	-1.80e-05***	3.86E-06
	[0.00117]	[0.000539]		[4.07e-06]	[2.76e-06]
Temp Spring (℃)	0.316***	0.278***	Prec Spring (cm)	0.00255	0.0118***
	[0.0474]	[0.0297]		[0.00192]	[0.00189]
Temp Spring sq (℃)	-0.00740***	-0.00590***	Prec Spring sq (cm)	1.39E-05	-5.96e-05***
	[0.00199]	[0.00143]		[1.65e-05]	[8.49e-06]
Temp Summer (℃)	-0.236***	-0.254***	Prec Summer (cm)	0.00434**	-0.000393
	[0.0475]	[0.0444]		[0.00184]	[0.00135]
Temp Summer sq (℃)	0.000594	-0.00236**	Prec Summer sq (cm)	-8.46E-06	1.57e-05**
	[0.00112]	[0.000926]		[9.93e-06]	[6.58e-06]
Temp Autumn (℃)	-0.0938	0.197***	Prec Autumn (cm)	-0.00458	-0.00508***
	[0.0849]	[0.0653]		[0.00346]	[0.00184]
Temp Autumn sq (℃)	0.0147***	0.00968***	Prec Autumn sq (cm)	-5.81E-06	1.26E-05
	[0.00312]	[0.00197]		[2.38e-05]	[9.56e-06]
Surface water ('000	0.0853***	0.0408***	Ground water ('000	0.0930***	0.0677***
l/day/ha)	[0.00509]	[0.00204]	l/day/ha)	[0.0161]	[0.00413]

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Coefficients of climate variables and of water use.

	Prob > F		Prob > F
temp win	0.0564	precip win	0.0000
temp win sq	0.7786	precip win sq	0.0000
temp spr	0.4176	precip spr	0.0003
temp spr sq	0.5055	precip spr sq	0.0000
temp sum	0.4915	precip sum	0.0267
temp sum sq	0.0001	precip sum sq	0.0295
temp aut	0.0001	precip aut	0.8964
temp aut sq	0.1351	precip aut sq	0.4680
surface water	0.0000	ground water	0.1253

Table 3. p-values for F-test on equality of coefficients between cropland and non-cropland.

Cropland - Precipitation

		USA	annual	0.33	(0.23 ; 0.43)		
			winter	0.26	(0.17 ; 0.36)		
			spring	0.13	(-0.02 ; 0.28)		
			summer	0.25	(0.17 ; 0.33)		
			autumn	-0.31	(-0.44 ; -0.19)		
CA	annual	0.35	(0.06 ; 0.63)	NR	annual	0.58	(0.34 ; 0.82)
	winter	0.3	(0.21 ; 0.4)		winter	0.23	(0.12 ; 0.35)
	spring	0.45	(0.25 ; 0.65)		spring	0.69	(0.44 ; 0.94)
	summer	-0.02	(-0.27 ; 0.23)		summer	0.08	(-0.09 ; 0.25)
	autumn	-0.39	(-0.59 ; -0.19)		autumn	-0.43	(-0.68 ; -0.18)
FL	annual	0.63	(0.4 ; 0.86)	NW	annual	0.29	(0.1 ; 0.47)
	winter	0.28	(0.18 ; 0.37)		winter	0.33	(0.22 ; 0.44)
	spring	0.09	(-0.06 ; 0.24)		spring	0.15	(0 ; 0.31)
	summer	0.51	(0.3 ; 0.72)		summer	0.06	(-0.12 ; 0.25)
	autumn	-0.25	(-0.37 ; -0.13)		autumn	-0.26	(-0.37 ; -0.14)
MW	annual	0.37	(0.26 ; 0.48)	SE	annual	0.14	(0.02 ; 0.26)
	winter	0.25	(0.15 ; 0.35)		winter	0.29	(0.2 ; 0.38)
	spring	0.15	(0 ; 0.3)		spring	-0.18	(-0.33 ; -0.03)
	summer	0.27	(0.19 ; 0.35)		summer	0.3	(0.22 ; 0.38)
	autumn	-0.31	(-0.43 ; -0.19)		autumn	-0.27	(-0.38 ; -0.16)
NE	annual	0.33	(0.22 ; 0.45)	SP	annual	0.32	(0.21 ; 0.44)
	winter	0.27	(0.18 ; 0.37)		winter	0.25	(0.15 ; 0.35)
	spring	0.04	(-0.1 ; 0.19)		spring	0.14	(-0.01 ; 0.3)
	summer	0.28	(0.2 ; 0.36)		summer	0.23	(0.15 ; 0.32)
	autumn	-0.26	(-0.38 ; -0.15)		autumn	-0.31	(-0.43 ; -0.19)
NP	annual	0.51	(0.36 ; 0.65)	SR	annual	0.68	(0.43 ; 0.93)
	winter	0.23	(0.1 ; 0.35)		winter	0.23	(0.11 ; 0.35)
	spring	0.42	(0.23 ; 0.61)		spring	0.78	(0.51 ; 1.05)
	summer	0.24	(0.16 ; 0.32)		summer	0.09	(-0.07 ; 0.26)
	autumn	-0.38	(-0.57 ; -0.19)		autumn	-0.43	(-0.68 ; -0.18)

Non-Cropland - Precipitations

		USA	annual	0.89	(0.72 ; 1.06)		
			winter	0.65	(0.45 ; 0.86)		
			spring	0.5	(0.14 ; 0.86)		
			summer	0.28	(0.15 ; 0.41)		
			autumn	-0.55	(-0.81 ; -0.28)		
CA	annual	0.8	(0.41 ; 1.2)	NR	annual	1.04	(0.66 ; 1.41)
	winter	0.47	(0.28 ; 0.66)		winter	0.79	(0.56 ; 1.03)
	spring	0.43	(0.17 ; 0.68)		spring	0.37	(0.14 ; 0.6)
	summer	0.42	(0.09 ; 0.76)		summer	0.37	(0.14 ; 0.59)
	autumn	-0.51	(-0.83 ; -0.2)		autumn	-0.49	(-0.91 ; -0.08)
FL	annual	0.67	(0.18 ; 1.17)	NW	annual	0.65	(0.38 ; 0.93)
	winter	0.6	(0.41 ; 0.8)		winter	0.35	(0.15 ; 0.55)
	spring	0.51	(0.14 ; 0.88)		spring	0.49	(0.15 ; 0.84)
	summer	0.14	(-0.22 ; 0.5)		summer	0.38	(0.13 ; 0.63)
	autumn	-0.58	(-0.99 ; -0.17)		autumn	-0.57	(-0.95 ; -0.19)
MW	annual	0.91	(0.72 ; 1.11)	SE	annual	0.79	(0.53 ; 1.05)
	winter	0.7	(0.49 ; 0.91)		winter	0.53	(0.34 ; 0.72)
	spring	0.5	(0.15 ; 0.84)		spring	0.57	(0.08 ; 1.07)
	summer	0.27	(0.13 ; 0.4)		summer	0.25	(0.1 ; 0.4)
	autumn	-0.55	(-0.81 ; -0.28)		autumn	-0.57	(-0.92 ; -0.22)
NE	annual	0.82	(0.56 ; 1.08)	SP	annual	0.94	(0.76 ; 1.12)
	winter	0.61	(0.41 ; 0.81)		winter	0.71	(0.49 ; 0.92)
	spring	0.52	(0.13 ; 0.92)		spring	0.5	(0.14 ; 0.85)
	summer	0.26	(0.12 ; 0.4)		summer	0.29	(0.16 ; 0.42)
	autumn	-0.57	(-0.94 ; -0.2)		autumn	-0.55	(-0.82 ; -0.28)
NP	annual	1.04	(0.81 ; 1.26)	SR	annual	1.03	(0.65 ; 1.41)
	winter	0.84	(0.59 ; 1.08)		winter	0.81	(0.57 ; 1.05)
	spring	0.43	(0.17 ; 0.69)		spring	0.35	(0.1 ; 0.59)
	summer	0.28	(0.15 ; 0.41)		summer	0.36	(0.15 ; 0.58)
	autumn	-0.52	(-0.81 ; -0.22)		autumn	-0.49	(-0.91 ; -0.08)

All values are percentages, already multiplied by 100. The % sign has been omitted to increase readability. 95% confidence intervals in parenthesis.

Table 4. Precipitations marginals, cropland and non-cropland, at US and regional level.

Cropland - Temperature

USA	annual	-2.28	(-5.14 ; 0.57)				
	winter	-24.88	(-27.07 ; -22.7)				
	spring	13.9	(11.11 ; 16.68)				
	summer	-36.15	(-39.17 ; -33.14)				
	autumn	44.86	(38.88 ; 50.83)				
CA	annual	-4.64	(-7.66 ; -1.62)	NR	annual	0.55	(-3.04 ; 4.15)
	winter	-30.75	(-33.47 ; -28.04)		winter	-18.98	(-21.36 ; -16.6)
	spring	12.99	(9.97 ; 16.01)		spring	21.41	(18.1 ; 24.71)
	summer	-35.29	(-38.34 ; -32.24)		summer	-33.5	(-37.06 ; -29.95)
	autumn	48.41	(42.59 ; 54.24)		autumn	31.63	(22.81 ; 40.45)
FL	annual	-9.9	(-13.05 ; -6.74)	NW	annual	-2.62	(-6.35 ; 1.1)
	winter	-38.05	(-41.98 ; -34.12)		winter	-25.06	(-27.26 ; -22.87)
	spring	3.16	(-3.75 ; 10.08)		spring	18.35	(15.79 ; 20.91)
	summer	-38.19	(-41.66 ; -34.72)		summer	-33.31	(-36.95 ; -29.68)
	autumn	63.18	(54.84 ; 71.52)		autumn	37.4	(30.15 ; 44.65)
MW	annual	1.41	(-1.29 ; 4.11)	SE	annual	-5.15	(-8.08 ; -2.22)
	winter	-20.85	(-23.09 ; -18.61)		winter	-28.76	(-31.23 ; -26.29)
	spring	17.13	(14.68 ; 19.57)		spring	10.37	(6.49 ; 14.26)
	summer	-35.46	(-38.5 ; -32.43)		summer	-37.03	(-40.16 ; -33.91)
	autumn	40.59	(34.02 ; 47.17)		autumn	50.27	(44.39 ; 56.15)
NE	annual	1.79	(-0.92 ; 4.51)	SP	annual	-5.41	(-8.36 ; -2.46)
	winter	-21.34	(-23.55 ; -19.12)		winter	-28.61	(-31.06 ; -26.15)
	spring	18.42	(15.85 ; 20.99)		spring	9.44	(5.2 ; 13.69)
	summer	-34.9	(-38.02 ; -31.78)		summer	-37.61	(-40.88 ; -34.34)
	autumn	39.61	(32.84 ; 46.37)		autumn	51.36	(45.4 ; 57.32)
NP	annual	2.32	(-0.56 ; 5.21)	SR	annual	-1.54	(-4.69 ; 1.62)
	winter	-17.32	(-19.88 ; -14.76)		winter	-23.16	(-25.32 ; -20.99)
	spring	18.79	(16.16 ; 21.42)		spring	17.8	(15.31 ; 20.29)
	summer	-35.37	(-38.42 ; -32.33)		summer	-34.79	(-37.93 ; -31.65)
	autumn	36.23	(28.69 ; 43.77)		autumn	38.61	(31.63 ; 45.58)

Non-Cropland - Temperature

USA	annual	2.17	(-0.63 ; 4.97)				
	winter	-20.03	(-25.15 ; -14.91)				
	spring	14.12	(9.02 ; 19.22)				
	summer	-20.83	(-26.41 ; -15.25)				
	autumn	28.92	(16.56 ; 41.27)				
CA	annual	-0.08	(-3.51 ; 3.36)	NR	annual	-2.87	(-6.48 ; 0.74)
	winter	-26.33	(-33.58 ; -19.07)		winter	-13.71	(-17.71 ; -9.71)
	spring	12.97	(7.68 ; 18.27)		spring	23.53	(17.41 ; 29.65)
	summer	-21.05	(-26.36 ; -15.74)		summer	-21.5	(-26.62 ; -16.38)
	autumn	34.33	(21.06 ; 47.59)		autumn	8.8	(-3.63 ; 21.24)
FL	annual	2.97	(-0.53 ; 6.47)	NW	annual	-4.5	(-8.29 ; -0.71)
	winter	-34.15	(-44.55 ; -23.75)		winter	-20.23	(-25.4 ; -15.05)
	spring	0.66	(-9.12 ; 10.43)		spring	19.7	(14.52 ; 24.88)
	summer	-20.32	(-26.89 ; -13.75)		summer	-21.55	(-26.68 ; -16.42)
	autumn	56.79	(37.27 ; 76.3)		autumn	17.58	(5.89 ; 29.26)
MW	annual	3.88	(0.99 ; 6.76)	SE	annual	2.05	(-0.78 ; 4.87)
	winter	-15.71	(-19.89 ; -11.53)		winter	-24.18	(-30.65 ; -17.72)
	spring	18.16	(13.18 ; 23.15)		spring	9.7	(3.56 ; 15.84)
	summer	-21.01	(-26.36 ; -15.65)		summer	-20.61	(-26.57 ; -14.65)
	autumn	22.43	(10.68 ; 34.18)		autumn	37.14	(23.28 ; 51.01)
NE	annual	3.34	(0.42 ; 6.27)	SP	annual	2.85	(0.07 ; 5.63)
	winter	-16.23	(-20.48 ; -11.97)		winter	-24.03	(-30.44 ; -17.62)
	spring	19.79	(14.59 ; 24.98)		spring	8.53	(2 ; 15.06)
	summer	-21.15	(-26.37 ; -15.93)		summer	-20.47	(-26.71 ; -14.22)
	autumn	20.93	(9.24 ; 32.63)		autumn	38.81	(24.56 ; 53.06)
NP	annual	3.09	(-0.05 ; 6.24)	SR	annual	-0.94	(-4.07 ; 2.2)
	winter	-11.92	(-15.93 ; -7.91)		winter	-18.18	(-22.82 ; -13.54)
	spring	20.25	(14.97 ; 25.53)		spring	19.01	(13.93 ; 24.08)
	summer	-21.03	(-26.36 ; -15.7)		summer	-21.18	(-26.38 ; -15.97)
	autumn	15.79	(4.04 ; 27.55)		autumn	19.41	(7.74 ; 31.08)

All values are percentages, already multiplied by 100. The % sign has been omitted to increase readability. 95% confidence intervals in parenthesis.

Table 5. Temperature marginals, cropland and non-cropland, at US and regional level.

16 GCM scenarios			B1 - 2030						B1 - 2065						B1 - 2100			
(% of land values)	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact
California	-6	-9	-22	27	13	5	-4	-4	-33	38	24	8	-12	-9	-38	29	19	5
Florida	-12	-13	-32	23	15	3	-9	-11	-37	16	16	6	-10	-15	-36	21	17	5
Midwest	6	8	-22	27	14	10	4	2	-32	50	20	9	-2	-3	-42	46	23	7
North East	4	3	-16	33	15	10	12	12	-20	55	22	10	5	4	-33	78	25	10
Northern Plains	8	7	-17	49	17	12	1	-5	-13	27	13	7	-1	-1	-25	36	18	8
North Rocky Mountains	-4	-9	-21	30	14	6	-10	-13	-26	19	12	4	-17	-17	-34	5	12	2
North West	-10	-11	-25	24	13	3	-17	-20	-43	21	15	1	-26	-27	-47	2	13	1
South East	-5	-3	-31	33	16	5	1	4	-40	32	21	9	-3	-4	-48	60	30	8
Southern Plains	-3	-5	-33	29	17	7	5	4	-37	79	28	9	4	2	-44	91	33	9
South Rocky Mountains	-1	-3	-25	21	14	6	0	-4	-26	40	18	7	1	-3	-19	37	17	7
United States	0	-1	-20	26	11	6	1	0	-23	20	12	8	-3	-5	-33	40	18	6

14 GCM scenarios			A2 - 2030						A2 - 2065						A2 - 2100			
(% of land values)	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact
California	-5	-2	-33	29	19	5	-9	-8	-38	13	14	5	-8	-8	-47	41	27	6
Florida	-2	-4	-31	27	16	6	-10	-16	-48	35	23	4	-20	-18	-56	21	23	2
Midwest	13	11	-18	61	22	9	1	-5	-50	128	44	7	-7	-5	-69	62	37	6
North East	13	16	-22	47	22	9	8	1	-42	89	38	7	7	10	-33	82	33	9
Northern Plains	10	7	-12	39	15	11	-3	-3	-51	65	26	7	-6	-3	-58	48	30	6
North Rocky Mountains	-7	-7	-31	9	12	5	-22	-21	-47	-5	13	0	-28	-27	-58	8	16	1
North West	-11	-11	-43	13	14	3	-25	-24	-49	11	18	1	-34	-34	-65	-8	17	0
South East	7	12	-24	40	22	9	-4	0	-57	58	29	7	-2	-9	-53	97	46	6
Southern Plains	9	8	-19	46	21	8	-1	-12	-45	66	28	6	3	5	-53	60	36	8
South Rocky Mountains	-2	-4	-21	15	10	5	-1	-3	-29	44	22	5	11	4	-33	77	32	8
United States	6	7	-9	26	12	9	-4	-6	-32	57	22	5	-5	-9	-42	52	28	5

20 GCM scenarios			A1B - 2030						A1B - 2065						A1B - 2100			
(% of land values)	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact	Mean	Median	Min	Max	Sd	Positive impact
California	-12	-14	-41	30	19	5	-6	-9	-42	39	20	7	-12	-19	-53	25	22	6
Florida	-3	-6	-25	22	15	8	-15	-18	-45	29	18	3	-14	-16	-38	36	20	4
Midwest	3	2	-23	46	17	10	-9	-13	-57	30	23	7	-10	-12	-50	49	26	7
North East	3	1	-32	38	17	12	0	5	-35	29	20	12	4	3	-31	64	24	11
Northern Plains	5	7	-30	27	16	13	-6	-7	-40	31	18	7	-12	-12	-46	15	20	7
North Rocky Mountains	-10	-10	-33	13	14	6	-18	-21	-40	6	13	2	-26	-26	-53	-3	14	0
North West	-15	-17	-42	17	14	2	-23	-24	-47	19	17	2	-37	-39	-55	-4	14	0
South East	0	-1	-36	39	19	10	-8	-9	-49	29	23	7	-5	-15	-48	76	31	8
Southern Plains	5	2	-27	48	21	10	-3	0	-44	40	20	10	-3	-6	-47	56	28	8
South Rocky Mountains	-2	-1	-23	22	11	8	2	1	-26	38	17	10	3	3	-32	59	23	10
United States	0	-1	-19	18	11	9	-7	-9	-24	23	14	6	-9	-17	-34	34	18	7

Notes: The column under the heading "positive impact" indicates the number of scenarios for which the impact is positive. 16 scenarios are available for the B1 SRES scenario, 14 for the A2 and 20 for the A1B.

Table 6. The impact of climate change on US agricultural land values, percentage of land value (%omitted for readability).

List of Figures

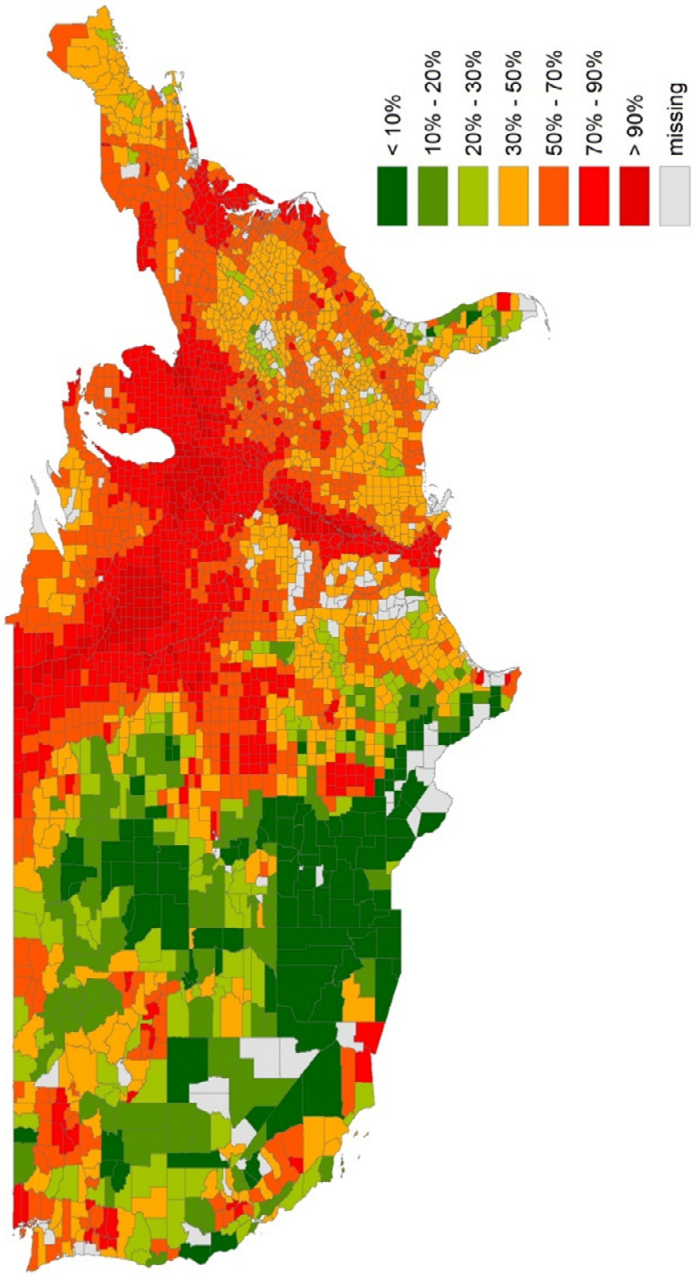
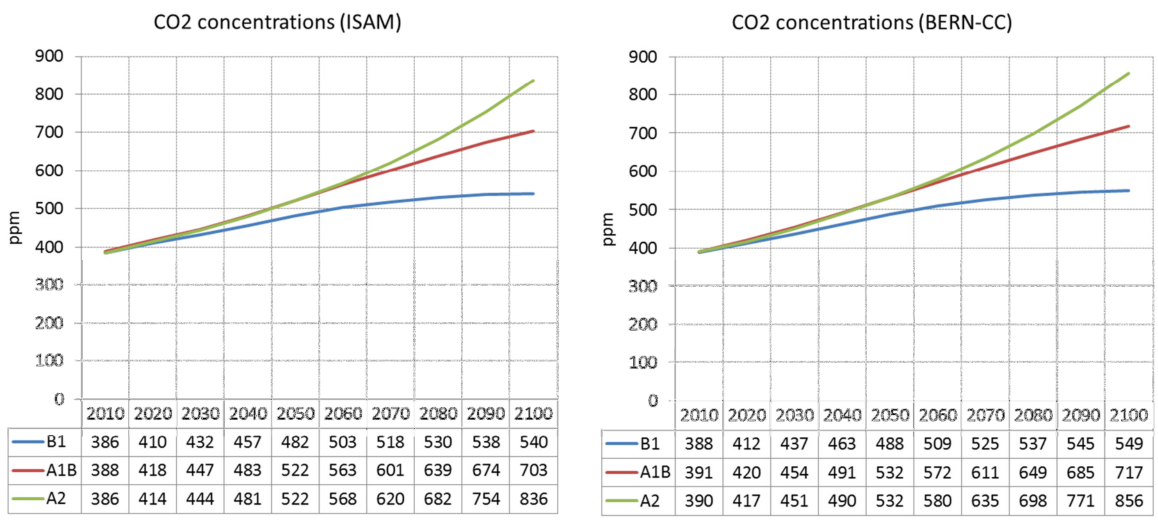


Figure 1. The distribution of cropland in the US.



CO2 concentrations (ISAM), ppm:

	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
B1	386	410	432	457	482	503	518	530	538	540
A1B	388	418	447	483	522	563	601	639	674	703
A2	386	414	444	481	522	568	620	682	754	836

CO2 concentrations (BERN-CC), ppm:

	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
B1	388	412	437	463	488	509	525	537	545	549
A1B	391	420	454	491	532	572	611	649	685	717
A2	390	417	451	490	532	580	635	698	771	856

Figure 2. CO2 concentrations used in the SRES scenarios according to the ISAM and BERN CC carbon cycle models.

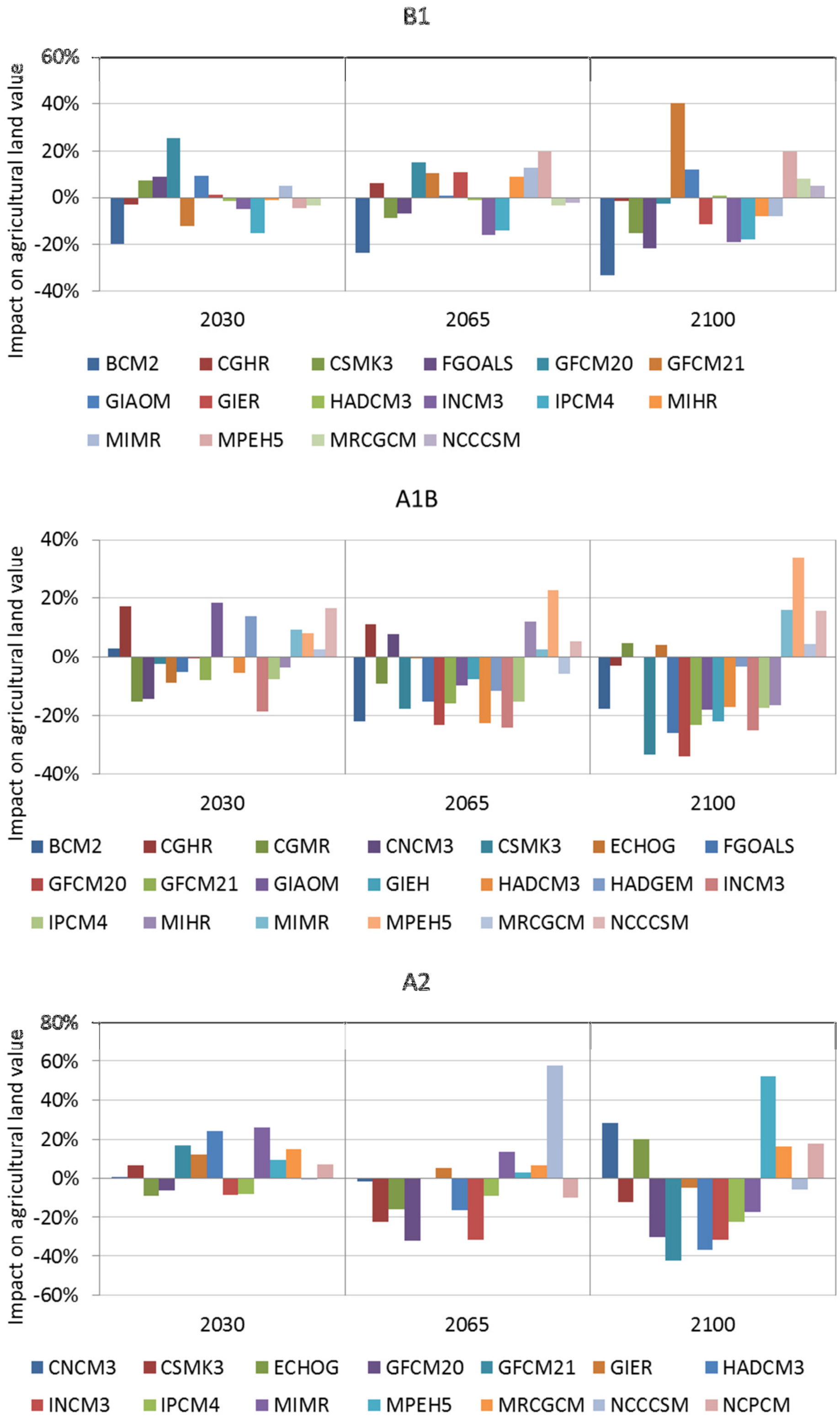


Figure 3. The impact of climate change on US agriculture according to the full set of B1, A1B and A1 scenarios, in 2030, 2065 and 2100.

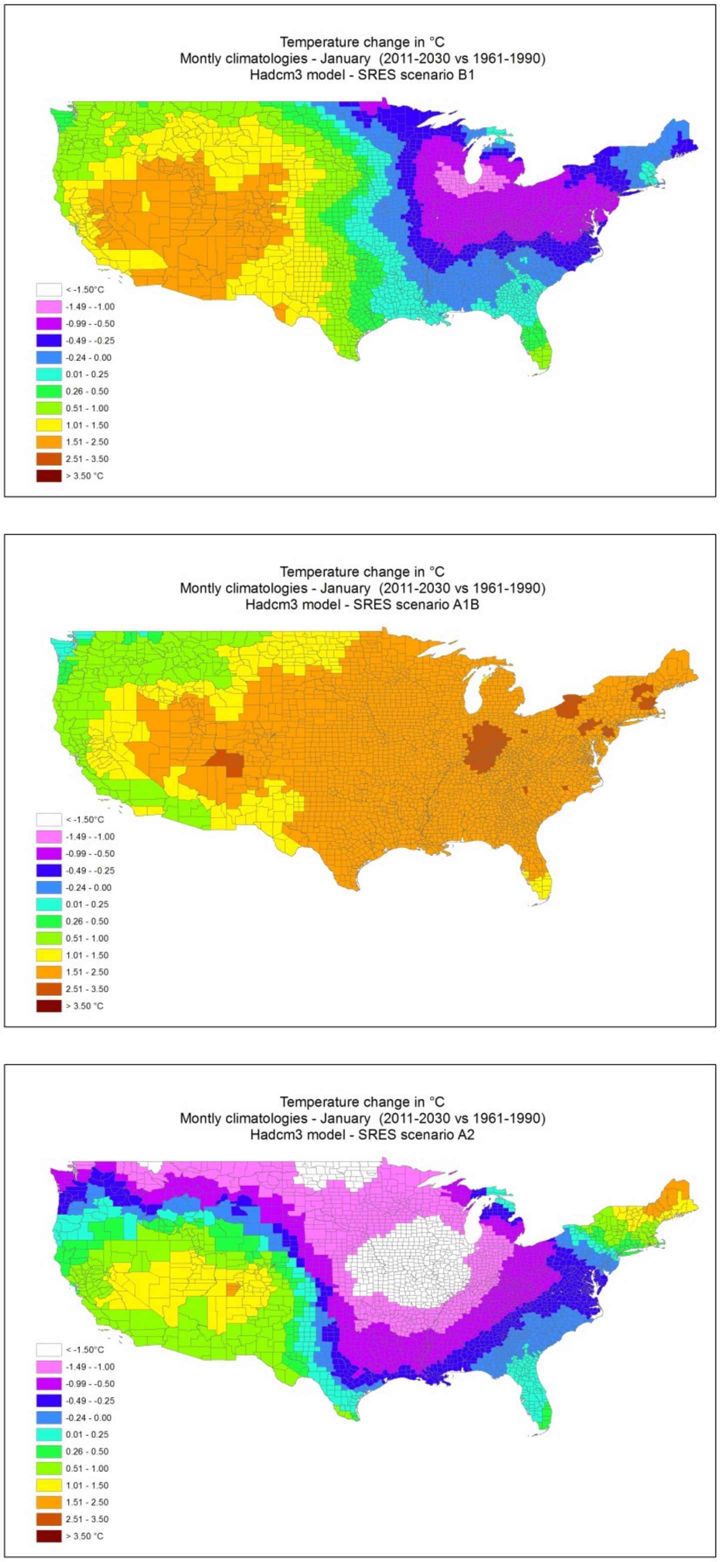


Figure 4. Three scenarios for temperature change in January, 2011-2030 with respect to 1961-1990, using the HADCM3 model to represent B1, A1B and A2 SRES emission scenarios.

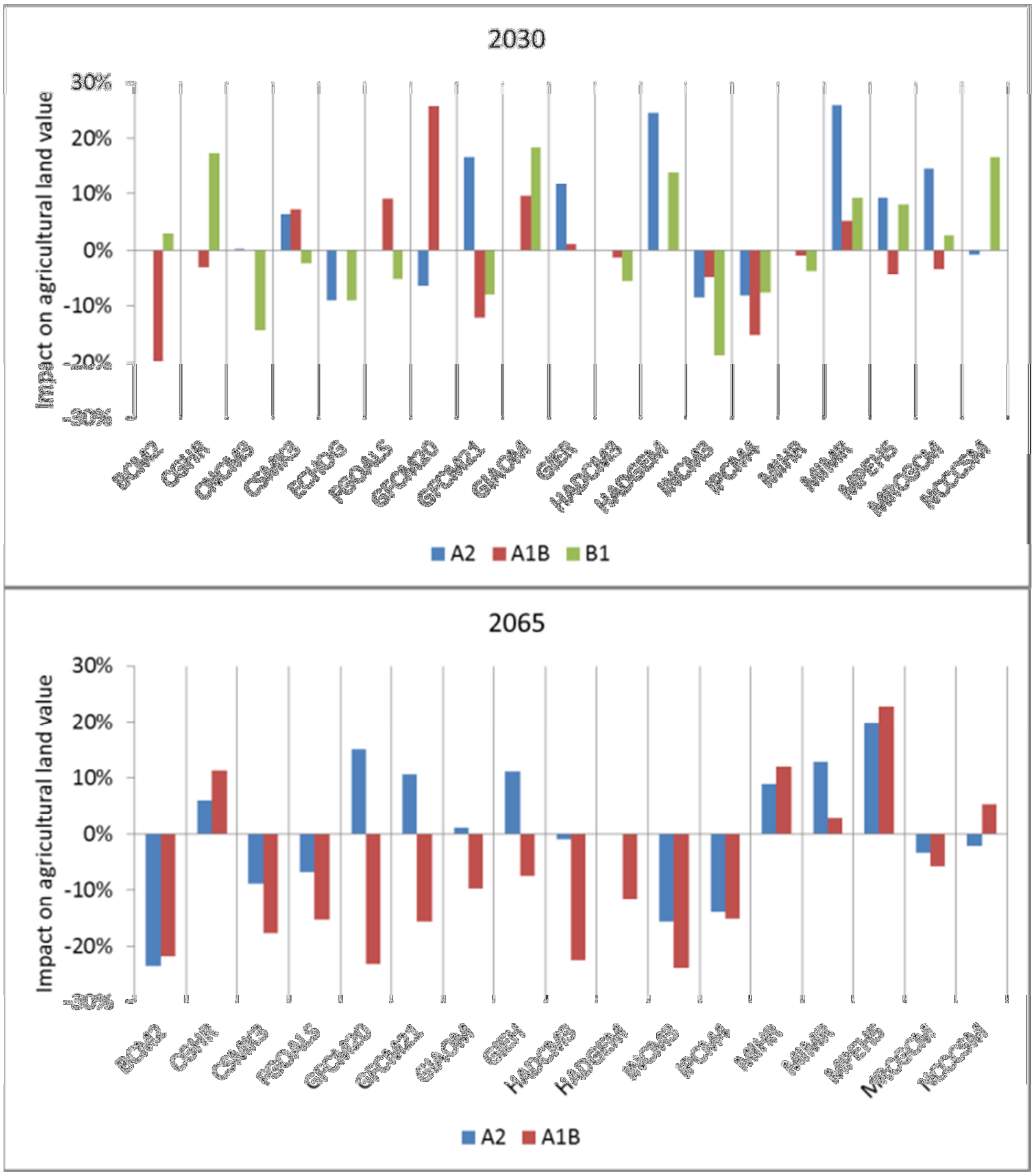


Figure 5. The implications of the “within models” uncertainty in 2030 and in 2065.

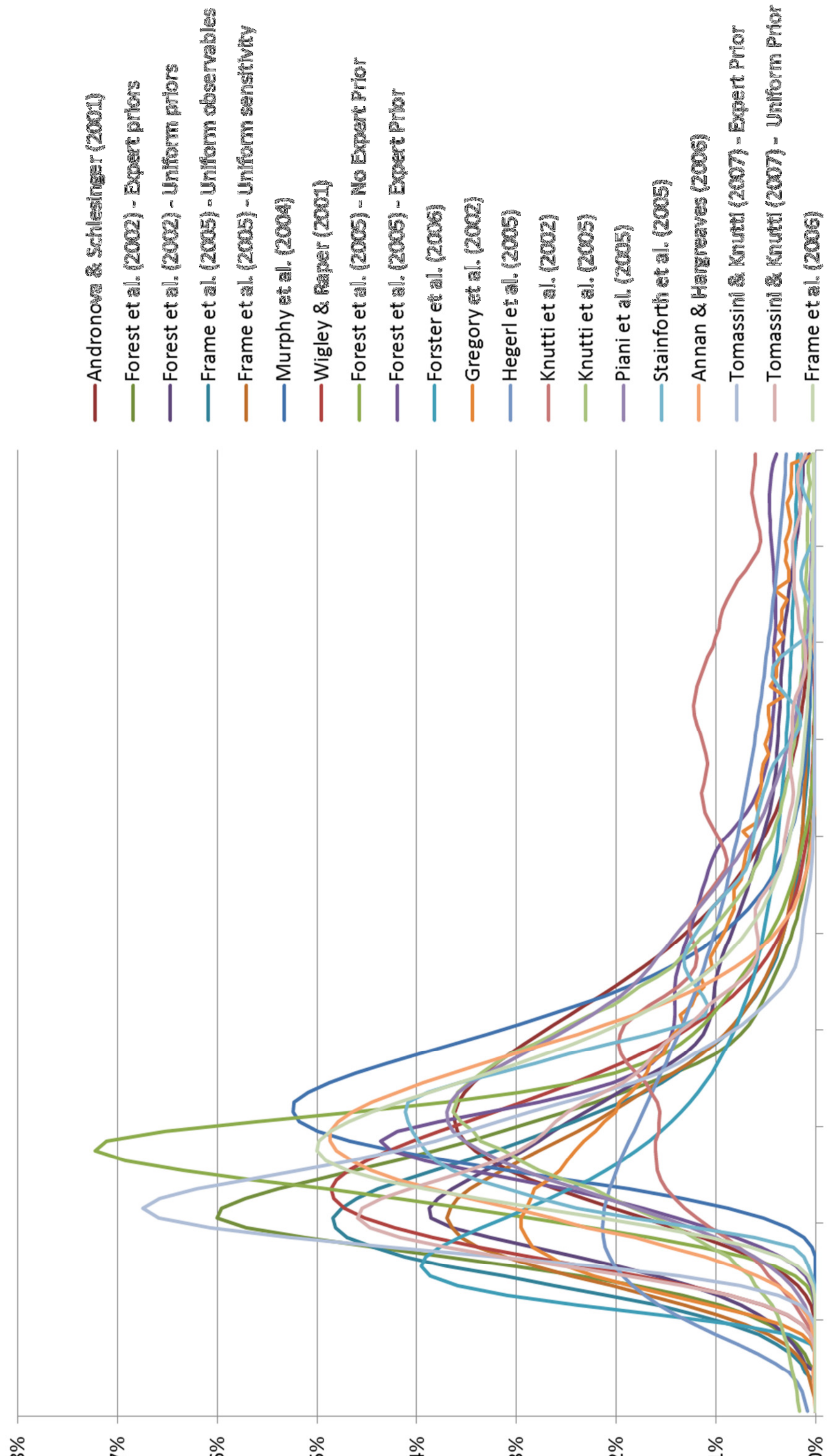
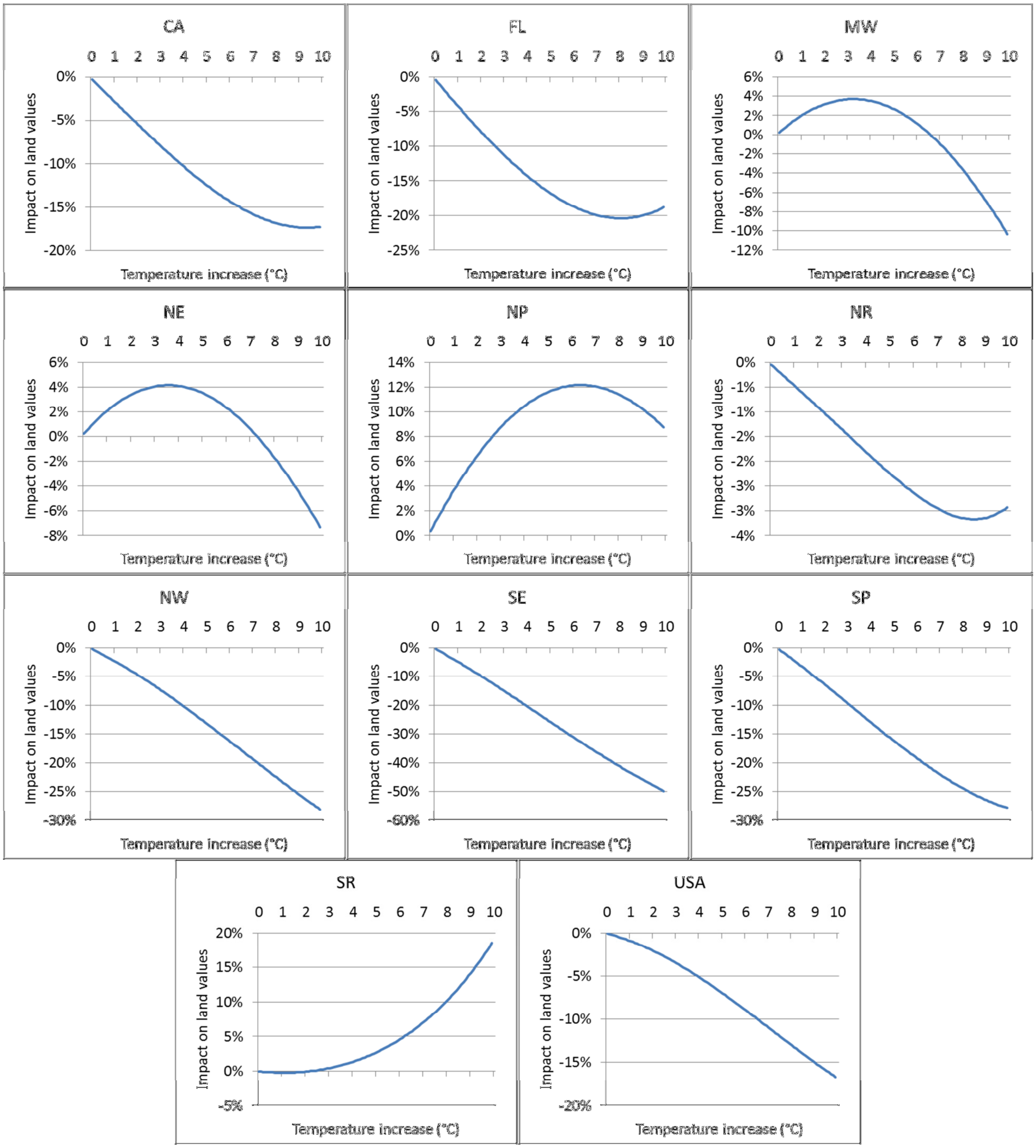


Figure 6. Probability density functions of climate sensitivity (Meinshausen et al. 2009).



Notes: CA, California; FL, Florida; MW, Midwest; NE, North East; NP, Northern Plains; NR, Northern Rockies; NW, North West; SE, South East; SP, Southern Plains; SR, Southern Rockies.

Figure 7. The impact of a uniform warming and increased rainfall scenario on US agriculture.

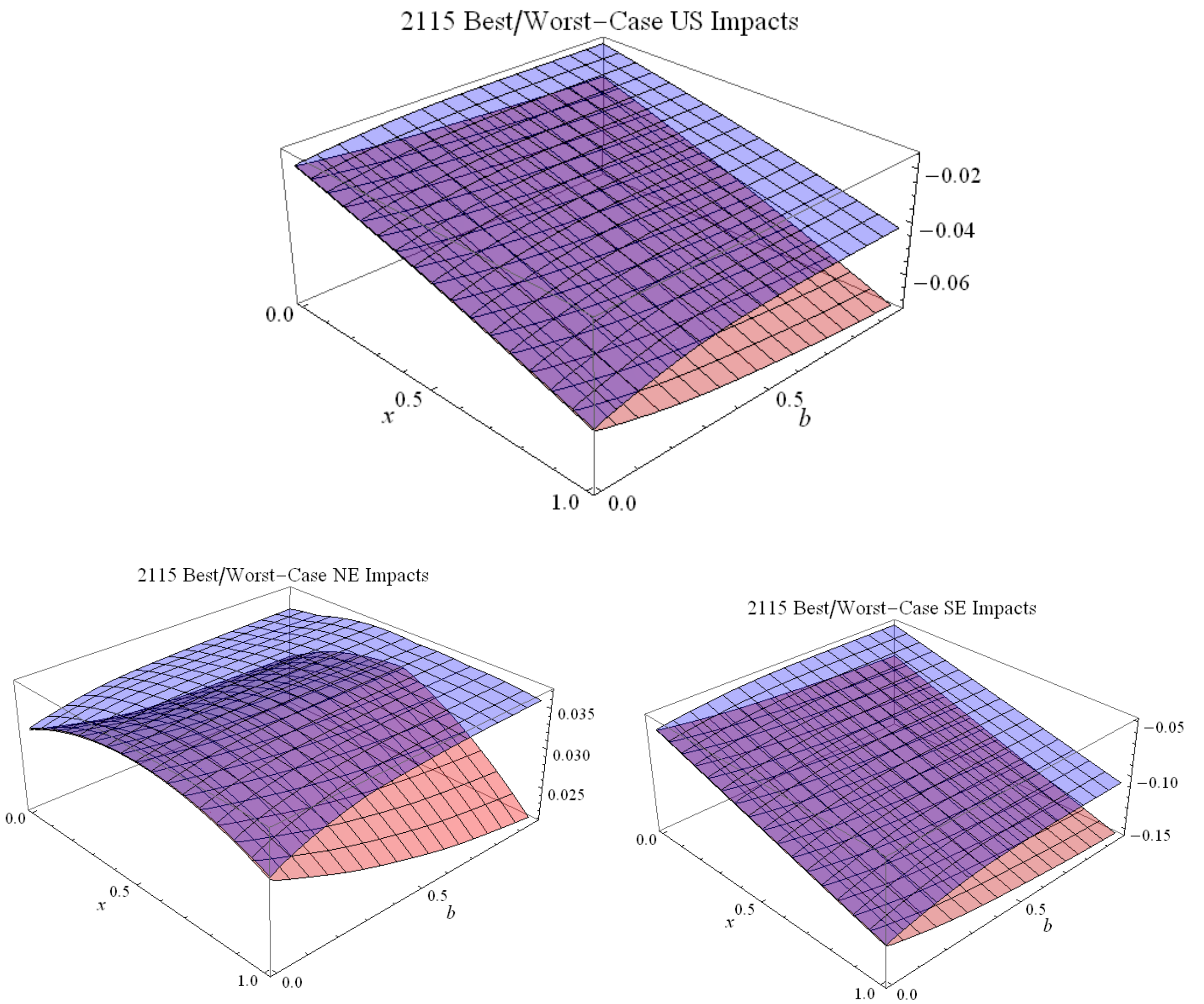


Figure 8. Plotting best- $\left(V_{max}(f(x)|b^2)\right)$ and worst-case $\left(V_{min}(f(x)|b^2)\right)$ agriculture impacts for the US, NE and SE as a function of b and x.

Appendix – Tables

	Non-Cropland	Cropland		Non-Cropland	Cropland
Temp Winter (℃)	-0.192***	-0.241***	Prec Winter (cm)	0.00900***	0.00212***
	[0.0250]	[0.0111]		[0.00134]	[0.000695]
Temp Winter sq (℃)	-0.00505***	-0.00471***	Prec Winter sq (cm)	-1.80e-05***	3.86E-06
	[0.00117]	[0.000539]		[4.07e-06]	[2.76e-06]
Temp Spring (℃)	0.316***	0.278***	Prec Spring (cm)	0.00255	0.0118***
	[0.0474]	[0.0297]		[0.00192]	[0.00189]
Temp Spring sq (℃)	-0.00740***	-0.00590***	Prec Spring sq (cm)	1.39E-05	-5.96e-05***
	[0.00199]	[0.00143]		[1.65e-05]	[8.49e-06]
Temp Summer (℃)	-0.236***	-0.254***	Prec Summer (cm)	0.00434**	-0.000393
	[0.0475]	[0.0444]		[0.00184]	[0.00135]
Temp Summer sq (℃)	0.000594	-0.00236**	Prec Summer sq (cm)	-8.46E-06	1.57e-05**
	[0.00112]	[0.000926]		[9.93e-06]	[6.58e-06]
Temp Autumn (℃)	-0.0938	0.197***	Prec Autumn (cm)	-0.00458	-0.00508***
	[0.0849]	[0.0653]		[0.00346]	[0.00184]
Temp Autumn sq (℃)	0.0147***	0.00968***	Prec Autumn sq (cm)	-5.81E-06	1.26E-05
	[0.00312]	[0.00197]		[2.38e-05]	[9.56e-06]
Surface water ('000	0.0853***	0.0408***	Ground water ('000	0.0930***	0.0677***
l/day/ha)	[0.00509]	[0.00204]	l/day/ha)	[0.0161]	[0.00413]
	All agricultural land			All agricultural land	
Income ('000 $)		0.000512	Salinity (%)		-0.0890***
		[0.00160]			[0.0339]
Pop. density (people/km^2)		0.00197***	Flooding (%)		-0.0907*
		[0.000129]			[0.0538]
Pop. density sq (people/km^2)		-1.14e-06***	Wet index (%)		0.168***
		[1.65e-07]			[0.0241]
Median house price ('000 $)		0.00678***	K-factor		-0.945***
		[0.000265]			[0.120]
Average farm size (ha)		-6.22e-05***	Lenght of slope		-6.30e-05*
		[1.15e-05]			[3.73e-05]
Average farm size (ha)		7.12e-10***	Sand (%)		0.0142
		[2.45e-10]			[0.0588]
Elevation (m)		-0.000185***	Clay (%)		0.0951**
		[6.89e-05]			[0.0388]
Latitude (DD)		0.00138	Moisture Level		0.270
		[0.0112]			[0.297]
Distance Met Areas (km)		-0.000691***	Permeability		-0.0250*
		[4.07e-05]			[0.0139]
1982 dummy		-0.0291**	1997 dummy		-0.378***
		[0.0147]			[0.0165]
1987 dummy		-0.383***	2002 dummy		-0.315***
		[0.0161]			[0.0183]
1992 dummy		-0.459***	Constant		8.432***
		[0.0171]			[0.906]
Adjusted R-sq	0.880				

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.

Table A1. Coefficients of all variables.

year	model	variable	season	min	p25	median	p75	max	mean
2020	CSMK3	tmp	win	0.01	0.29	0.40	0.57	1.41	0.46
2020	GFCM20	tmp	win	0.01	0.20	0.33	0.54	1.26	0.39
2020	GFCM21	tmp	win	0.04	0.50	0.68	0.88	2.22	0.76
2020	HADCM3	tmp	win	0.27	0.84	1.25	1.62	2.94	1.29
2020	INCM3	tmp	win	0.01	0.32	0.62	0.91	1.79	0.69
2020	IPCM4	tmp	win	0.11	0.42	0.56	0.71	1.33	0.59
2020	MIMR	tmp	win	0.00	0.22	0.34	0.44	0.76	0.34
2020	MPEH5	tmp	win	0.02	0.38	0.62	0.83	1.28	0.61
2020	MRCGCM	tmp	win	0.17	0.34	0.46	0.78	1.33	0.59
2020	NCCCSM	tmp	win	0.05	0.33	0.70	0.91	1.91	0.68
2020	CSMK3	tmp	spr	0.01	0.25	0.43	0.62	0.93	0.44
2020	GFCM20	tmp	spr	0.02	0.27	0.46	0.62	0.92	0.45
2020	GFCM21	tmp	spr	0.02	0.36	0.52	0.62	0.96	0.49
2020	HADCM3	tmp	spr	0.10	0.63	0.81	0.97	1.19	0.78
2020	INCM3	tmp	spr	0.05	0.26	0.42	0.58	1.00	0.43
2020	IPCM4	tmp	spr	0.04	0.25	0.41	0.56	0.89	0.41
2020	MIMR	tmp	spr	0.11	0.25	0.33	0.47	0.84	0.37
2020	MPEH5	tmp	spr	0.01	0.19	0.47	0.90	1.30	0.55
2020	MRCGCM	tmp	spr	0.02	0.27	0.40	0.49	1.01	0.39
2020	NCCCSM	tmp	spr	0.01	0.29	0.39	0.46	0.82	0.37
2020	CSMK3	tmp	sum	0.01	0.24	0.36	0.53	1.09	0.39
2020	GFCM20	tmp	sum	0.01	0.30	0.62	0.99	1.93	0.70
2020	GFCM21	tmp	sum	0.01	0.38	0.53	0.75	1.55	0.60
2020	HADCM3	tmp	sum	0.06	0.43	0.70	0.93	2.06	0.70
2020	INCM3	tmp	sum	0.00	0.15	0.23	0.33	0.54	0.24
2020	IPCM4	tmp	sum	0.00	0.19	0.35	0.48	0.79	0.35
2020	MIMR	tmp	sum	0.02	0.18	0.28	0.49	0.75	0.33
2020	MPEH5	tmp	sum	0.02	0.30	0.41	0.54	1.08	0.44
2020	MRCGCM	tmp	sum	0.04	0.24	0.30	0.56	1.20	0.40
2020	NCCCSM	tmp	sum	0.00	0.16	0.34	0.55	1.20	0.38
2020	CSMK3	tmp	aut	0.01	0.32	0.43	0.56	0.91	0.44
2020	GFCM20	tmp	aut	0.01	0.33	0.51	0.72	1.19	0.53
2020	GFCM21	tmp	aut	0.02	0.30	0.44	0.76	1.32	0.54
2020	HADCM3	tmp	aut	0.09	0.51	0.63	0.76	1.19	0.63
2020	INCM3	tmp	aut	0.02	0.25	0.41	0.54	0.84	0.40
2020	IPCM4	tmp	aut	0.02	0.24	0.31	0.44	0.77	0.35
2020	MIMR	tmp	aut	0.00	0.14	0.23	0.36	0.53	0.25
2020	MPEH5	tmp	aut	0.03	0.48	0.71	0.95	1.66	0.71
2020	MRCGCM	tmp	aut	0.02	0.19	0.26	0.34	0.60	0.26
2020	NCCCSM	tmp	aut	0.00	0.15	0.22	0.30	0.58	0.23

Table A2. Ratio between the maximum and the minimum prediction of temperature change in 2030 (2011-2030) with respect to 1961-1990 using models for which the B1, A1B and A2 scenarios are available.

year	model	variable	season	min	p25	median	p75	max	mean
2020	CSMK3	pre	win	-3597	-1.40	0.20	2.28	5122	1.43
2020	GFCM20	pre	win	-6991	-1.44	1.39	2.91	2377	-0.03
2020	GFCM21	pre	win	-4497	-1.76	-0.31	1.90	1191	-7.37
2020	HADCM3	pre	win	-690	-1.64	-0.36	1.62	2139	0.21
2020	INCM3	pre	win	-2968	0.53	1.54	2.16	2160	1.88
2020	IPCM4	pre	win	-7052	-0.58	1.21	2.34	252	-5.57
2020	MIMR	pre	win	-1577	-0.23	0.60	2.24	3975	1.45
2020	MPEH5	pre	win	-3770	-2.26	-0.51	3.22	4933	5.15
2020	MRCGCM	pre	win	-3496	-0.45	2.19	4.19	1574	1.35
2020	NCCCSM	pre	win	-48	-0.59	-0.06	0.23	8311	1.86
2020	CSMK3	pre	spr	-9175	-1.13	-0.02	1.62	10363	2.66
2020	GFCM20	pre	spr	-2556	-0.22	1.29	2.54	28170	12.24
2020	GFCM21	pre	spr	-5091	0.23	0.53	2.19	366	0.51
2020	HADCM3	pre	spr	-363	-0.88	-0.05	1.25	4348	0.82
2020	INCM3	pre	spr	-1418	-0.33	0.27	1.16	826	-0.29
2020	IPCM4	pre	spr	-3855	-0.59	0.25	0.79	18801	0.51
2020	MIMR	pre	spr	-43783	-1.96	0.09	0.65	1565	-33.10
2020	MPEH5	pre	spr	-2657	-1.27	0.05	1.51	5647	6.67
2020	MRCGCM	pre	spr	-872	-0.17	0.18	1.29	10357	2.85
2020	NCCCSM	pre	spr	-1420	-0.76	0.17	1.55	1724	1.58
2020	CSMK3	pre	sum	-8821	-2.12	0.06	3.17	953	-2.16
2020	GFCM20	pre	sum	-652	-0.98	-0.27	0.43	6533	5.77
2020	GFCM21	pre	sum	-2291	-0.42	0.12	0.55	961	0.65
2020	HADCM3	pre	sum	-3045	-0.31	0.03	0.34	981	-0.32
2020	INCM3	pre	sum	-233	-0.17	0.36	0.58	905	1.34
2020	IPCM4	pre	sum	-63904	-1.00	-0.14	0.27	7049	-16.78
2020	MIMR	pre	sum	-674	-0.10	0.21	0.59	331	-0.75
2020	MPEH5	pre	sum	-1565	-1.08	-0.08	1.51	1144	-0.01
2020	MRCGCM	pre	sum	-2361	-1.73	-0.26	1.83	347	-1.46
2020	NCCCSM	pre	sum	-494	-0.41	0.27	1.30	3486	1.61
2020	CSMK3	pre	aut	-5723	-1.97	0.04	3.47	4713	0.65
2020	GFCM20	pre	aut	-763	-1.26	-0.09	0.43	4696	1.66
2020	GFCM21	pre	aut	-492	-1.28	-0.38	0.23	1997	-0.13
2020	HADCM3	pre	aut	-16176	-1.68	-0.20	2.47	1044	-5.98
2020	INCM3	pre	aut	-437	-0.57	0.04	0.50	443	1.01
2020	IPCM4	pre	aut	-1480	-2.32	0.08	2.32	1242	-1.62
2020	MIMR	pre	aut	-206	-0.47	0.21	0.62	532	0.40
2020	MPEH5	pre	aut	-5885	-1.33	-0.28	0.30	7651	0.53
2020	MRCGCM	pre	aut	-2581	-1.49	1.51	3.20	878	0.19
2020	NCCCSM	pre	aut	-1374	-0.89	-0.17	0.36	4601	1.01

Table A3. Ratio between the maximum and the minimum prediction of precipitation change in 2030 (2011-2030) with respect to 1961-1990 using models for which the B1, A1B and A2 scenarios are available.

year	model	variable	season	min	p25	median	p75	max	mean
2055	CNCM3	tmp	win	0.00	0.17	0.28	0.37	0.60	0.27
2055	CSMK3	tmp	win	0.03	0.27	0.42	0.69	1.41	0.52
2055	ECHOG	tmp	win	0.00	0.27	0.50	0.75	1.13	0.52
2055	GFCM20	tmp	win	0.00	0.22	0.43	0.58	0.85	0.40
2055	GFCM21	tmp	win	0.00	0.20	0.45	0.68	0.97	0.44
2055	HADCM3	tmp	win	0.00	0.45	0.67	0.99	2.05	0.77
2055	INCM3	tmp	win	0.00	0.52	0.78	0.95	1.47	0.74
2055	IPCM4	tmp	win	0.14	0.45	0.70	1.12	1.64	0.78
2055	MIMR	tmp	win	0.00	0.07	0.16	0.25	0.45	0.16
2055	MPEH5	tmp	win	0.00	0.37	0.89	1.25	1.89	0.83
2055	MRCGCM	tmp	win	0.13	0.39	0.52	0.61	0.83	0.50
2055	NCCCSM	tmp	win	0.00	0.06	0.14	0.31	0.95	0.23
2055	CNCM3	tmp	spr	0.00	0.15	0.25	0.33	0.52	0.24
2055	CSMK3	tmp	spr	0.00	0.09	0.17	0.30	0.75	0.21
2055	ECHOG	tmp	spr	0.00	0.11	0.27	0.36	0.73	0.26
2055	GFCM20	tmp	spr	0.00	0.18	0.44	0.70	1.33	0.47
2055	GFCM21	tmp	spr	0.00	0.27	0.40	0.62	1.15	0.46
2055	HADCM3	tmp	spr	0.00	0.37	0.50	0.58	1.38	0.48
2055	INCM3	tmp	spr	0.00	0.06	0.16	0.28	0.57	0.18
2055	IPCM4	tmp	spr	0.00	0.10	0.21	0.33	0.83	0.24
2055	MIMR	tmp	spr	0.00	0.10	0.20	0.39	0.76	0.25
2055	MPEH5	tmp	spr	0.00	0.28	0.63	1.01	2.17	0.70
2055	MRCGCM	tmp	spr	0.00	0.03	0.08	0.16	0.46	0.12
2055	NCCCSM	tmp	spr	0.00	0.07	0.16	0.23	0.51	0.17
2055	CNCM3	tmp	sum	0.00	0.09	0.17	0.27	0.54	0.19
2055	CSMK3	tmp	sum	0.00	0.13	0.39	0.68	1.18	0.43
2055	ECHOG	tmp	sum	0.00	0.06	0.11	0.21	0.57	0.15
2055	GFCM20	tmp	sum	0.00	0.10	0.24	0.55	1.14	0.34
2055	GFCM21	tmp	sum	0.00	0.27	0.66	1.07	1.61	0.68
2055	HADCM3	tmp	sum	0.00	0.16	0.31	0.55	1.28	0.36
2055	INCM3	tmp	sum	0.00	0.29	0.45	0.63	1.13	0.45
2055	IPCM4	tmp	sum	0.00	0.05	0.11	0.25	0.81	0.19
2055	MIMR	tmp	sum	0.00	0.11	0.24	0.48	1.22	0.33
2055	MPEH5	tmp	sum	0.00	0.21	0.37	0.55	0.99	0.38
2055	MRCGCM	tmp	sum	0.00	0.13	0.22	0.30	2.39	0.23
2055	NCCCSM	tmp	sum	0.00	0.10	0.19	0.31	0.69	0.22
2055	CNCM3	tmp	aut	0.00	0.13	0.18	0.23	0.49	0.18
2055	CSMK3	tmp	aut	0.14	0.36	0.44	0.54	0.89	0.45
2055	ECHOG	tmp	aut	0.00	0.08	0.15	0.24	0.58	0.17
2055	GFCM20	tmp	aut	0.00	0.55	0.66	0.81	1.29	0.67
2055	GFCM21	tmp	aut	0.00	0.23	0.43	0.64	1.08	0.45
2055	HADCM3	tmp	aut	0.00	0.11	0.30	0.85	1.40	0.47
2055	INCM3	tmp	aut	0.00	0.11	0.22	0.33	0.51	0.22
2055	IPCM4	tmp	aut	0.00	0.31	0.46	0.58	0.86	0.45
2055	MIMR	tmp	aut	0.00	0.09	0.18	0.31	0.51	0.21
2055	MPEH5	tmp	aut	0.01	0.68	0.79	1.01	1.35	0.82
2055	MRCGCM	tmp	aut	0.00	0.08	0.18	0.33	0.77	0.21
2055	NCCCSM	tmp	aut	0.00	0.29	0.56	0.78	1.37	0.56

Table A4. Ratio between the maximum and the minimum prediction of temperature change in 2065 (2046-2065) with respect to 1961-1990 using models for which the A1B and A2 scenarios are available.

year	model	variable	season	min	p25	median	p75	max	mean
2055	CNCM3	pre	win	-298	0.42	1.24	2.08	153	1.25
2055	CSMK3	pre	win	-1293	0.28	1.19	1.71	469	0.28
2055	ECHOG	pre	win	-1320	-1.68	1.00	1.66	52729	12.08
2055	GFCM20	pre	win	-1960	-1.05	1.12	2.27	891	0.13
2055	GFCM21	pre	win	-1021	-0.75	1.25	2.16	3813	3.63
2055	HADCM3	pre	win	-398	-0.10	1.37	2.36	398	1.41
2055	INCM3	pre	win	-63	0.59	1.39	2.51	241	2.14
2055	IPCM4	pre	win	-3037	0.49	1.05	1.58	2869	1.26
2055	MIMR	pre	win	-11273	0.62	0.98	1.32	2115	-0.78
2055	MPEH5	pre	win	-487	1.24	1.74	2.58	755	1.85
2055	MRCGCM	pre	win	-772	1.00	1.29	1.98	1799	1.90
2055	NCCCSM	pre	win	-613	-0.17	0.29	0.73	911	1.28
2055	CNCM3	pre	spr	-468	0.68	0.97	1.68	190	0.82
2055	CSMK3	pre	spr	-598	0.06	0.70	1.35	1820	0.37
2055	ECHOG	pre	spr	-3037	0.00	0.54	0.92	3816	1.00
2055	GFCM20	pre	spr	-1525	0.36	0.84	1.35	13630	5.42
2055	GFCM21	pre	spr	-872	0.64	1.07	1.40	3315	0.83
2055	HADCM3	pre	spr	-122	0.27	0.88	1.44	216	1.38
2055	INCM3	pre	spr	-1419	0.06	0.85	1.61	1704	3.14
2055	IPCM4	pre	spr	-74	0.24	0.66	0.97	45	1.02
2055	MIMR	pre	spr	-326	0.60	0.83	1.15	23638	4.13
2055	MPEH5	pre	spr	-1162	-0.74	0.62	1.32	549	-0.61
2055	MRCGCM	pre	spr	-1725	0.24	1.09	1.79	9994	2.49
2055	NCCCSM	pre	spr	-180	0.53	1.18	1.82	1420	1.26
2055	CNCM3	pre	sum	-315	0.61	0.88	1.20	728	0.99
2055	CSMK3	pre	sum	-5772	-0.32	0.78	1.96	821	-6.58
2055	ECHOG	pre	sum	-526	0.69	1.12	1.65	435	1.18
2055	GFCM20	pre	sum	-454	0.43	0.81	0.93	297	0.67
2055	GFCM21	pre	sum	-157	0.60	0.82	0.94	78	0.68
2055	HADCM3	pre	sum	-919	0.20	0.67	0.95	209	0.39
2055	INCM3	pre	sum	-76	0.49	0.67	0.84	102	0.58
2055	IPCM4	pre	sum	-2073	-0.10	0.51	0.81	1116	-0.04
2055	MIMR	pre	sum	-3	0.66	0.80	0.91	11	0.76
2055	MPEH5	pre	sum	-4838	-0.14	1.05	1.81	2488	-6.01
2055	MRCGCM	pre	sum	-1689	0.29	1.03	2.09	638	-0.07
2055	NCCCSM	pre	sum	-9736	0.61	1.15	1.58	136	-1.93
2055	CNCM3	pre	aut	-60	0.32	0.62	1.19	773	0.92
2055	CSMK3	pre	aut	-9152	0.04	1.16	2.19	1718	0.49
2055	ECHOG	pre	aut	-544	0.20	0.65	0.97	1264	1.55
2055	GFCM20	pre	aut	-391	0.40	0.73	0.96	1070	0.87
2055	GFCM21	pre	aut	-4230	-0.46	0.49	1.18	5791	2.57
2055	HADCM3	pre	aut	-541	1.08	1.49	2.74	587	2.32
2055	INCM3	pre	aut	-136	0.09	0.70	0.96	725	1.45
2055	IPCM4	pre	aut	-79	0.00	0.71	1.46	469	1.48
2055	MIMR	pre	aut	-163	0.18	0.50	0.80	284	0.31
2055	MPEH5	pre	aut	-4461	-0.76	0.25	1.56	2066	-0.88
2055	MRCGCM	pre	aut	-848	-0.03	0.99	1.56	507	-0.88
2055	NCCCSM	pre	aut	-864	-0.94	0.04	0.69	2160	-0.63

Table A5. Ratio between the maximum and the minimum prediction of precipitation change in 2065 (2046-2065) with respect to 1961-1990 using models for which the A1B and A2 scenarios are available.

TEMPERATURE - A2- 2100 (2080-2100 climatology with respect to 1961-1990 - °C)

	Winter									Spring								
	min	p5	p25	p50	p75	p95	max	mean	sd	min	p5	p25	p50	p75	p95	max	mean	sd
CNCM3	1.7	2.2	3.3	3.8	4.3	5.5	6.8	3.8	0.9	1.5	2.4	3.7	4.5	5.0	6.1	6.7	4.4	1.1
CSMK3	2.0	2.3	3.2	3.6	4.6	6.9	7.5	4.0	1.3	1.9	2.1	2.4	2.7	3.0	3.5	3.8	2.7	0.4
ECHOG	2.5	3.1	3.6	4.0	4.4	5.8	6.8	4.1	0.8	2.5	3.3	3.9	4.3	4.7	5.1	5.3	4.3	0.5
GFCM20	2.4	2.7	3.1	3.7	4.3	5.9	6.8	3.8	1.0	1.8	2.7	4.1	4.5	4.7	5.6	5.8	4.4	0.8
GFCM21	1.7	2.0	2.5	3.0	3.4	4.0	4.9	3.0	0.6	2.0	2.5	3.7	4.4	5.0	5.7	6.1	4.3	1.0
GIER	0.7	1.1	2.0	2.7	3.1	3.6	4.0	2.5	0.8	-0.1	0.6	2.3	3.1	3.4	5.2	5.9	2.9	1.2
HADCM3	2.3	3.1	3.6	4.0	4.5	4.9	5.1	4.0	0.6	2.3	3.4	4.3	4.9	5.2	5.9	6.3	4.8	0.7
INCM3	1.9	2.4	4.0	4.8	5.3	5.9	7.0	4.6	1.1	3.0	3.1	3.5	4.0	4.4	4.8	5.6	4.0	0.5
IPCM4	2.3	4.3	6.1	7.0	7.4	8.0	8.8	6.6	1.1	2.7	4.1	5.3	6.1	6.6	7.8	8.4	6.0	1.0
MIMR	3.1	4.1	5.2	5.8	6.5	7.7	8.2	5.8	1.0	2.8	4.2	5.6	6.1	6.5	7.9	9.0	6.1	1.0
MPEH5	2.9	3.2	3.6	4.0	4.4	5.2	5.9	4.1	0.6	2.5	2.9	3.6	3.9	4.1	4.7	5.1	3.9	0.5
MRCGCM	1.7	2.1	2.6	2.9	3.5	4.7	5.7	3.1	0.8	1.5	2.0	2.6	3.2	3.6	4.1	4.6	3.1	0.6
NCCCSM	2.6	3.3	4.1	4.6	5.0	6.1	7.4	4.6	0.8	2.8	3.9	4.3	4.8	5.2	5.8	6.5	4.8	0.6
NCPCM	1.0	1.2	1.8	2.4	3.2	4.2	5.3	2.5	0.9	1.7	1.8	2.1	2.3	2.5	2.7	3.0	2.3	0.3
	Summer									Autumn								
	min	p5	p25	p50	p75	p95	max	mean	sd	min	p5	p25	p50	p75	p95	max	mean	sd
CNCM3	3.1	4.1	4.8	5.5	6.2	7.2	7.8	5.5	1.0	3.1	4.1	5.0	5.5	5.9	6.9	7.3	5.5	0.8
CSMK3	2.1	2.9	3.2	3.4	3.7	4.3	4.8	3.5	0.4	2.6	2.9	3.4	3.8	4.1	4.3	4.7	3.7	0.4
ECHOG	3.1	3.7	4.7	5.6	6.2	7.2	7.6	5.5	1.0	3.2	4.0	4.8	5.6	6.3	6.7	7.0	5.5	0.9
GFCM20	3.5	4.7	6.3	7.7	8.9	10.4	10.7	7.6	1.7	3.1	4.1	5.3	6.0	6.4	7.1	7.4	5.8	0.9
GFCM21	3.1	4.6	6.4	7.4	8.4	9.0	9.6	7.2	1.4	2.8	3.7	4.5	4.9	5.4	5.9	6.4	4.9	0.7
GIER	2.5	3.0	3.3	4.0	5.0	5.7	6.5	4.2	0.9	1.2	2.1	3.1	3.6	3.9	4.8	5.1	3.5	0.8
HADCM3	3.4	5.6	6.7	7.3	7.8	8.3	9.9	7.2	0.9	3.6	4.9	5.3	5.6	5.8	6.4	6.5	5.6	0.4
INCM3	3.2	4.0	4.9	5.6	6.1	6.5	6.9	5.4	0.8	3.0	3.6	4.5	4.8	5.0	5.3	5.6	4.7	0.5
IPCM4	3.3	4.3	5.2	5.5	5.7	5.9	6.3	5.4	0.5	2.8	4.2	5.3	5.8	6.1	6.7	7.6	5.7	0.8
MIMR	3.7	5.0	6.0	7.1	7.9	8.6	9.4	6.9	1.2	3.6	4.8	5.8	6.3	7.0	7.8	8.1	6.4	0.9
MPEH5	3.4	3.8	4.1	4.5	4.8	5.2	5.5	4.5	0.4	3.3	4.0	4.9	5.1	5.5	5.8	6.0	5.1	0.5
MRCGCM	2.6	2.9	3.2	3.3	3.5	4.0	4.4	3.4	0.3	2.3	2.6	3.3	3.7	3.9	4.2	4.4	3.6	0.5
NCCCSM	3.1	3.9	5.0	5.7	6.4	7.5	8.0	5.7	1.0	3.2	4.2	4.8	5.2	5.6	6.0	6.2	5.2	0.6
NCPCM	1.9	2.2	2.5	2.8	3.2	4.0	4.2	2.9	0.5	2.0	2.6	2.8	3.0	3.3	3.5	3.9	3.0	0.3

Table A6. Distribution of warming across all US counties that belong to our panel. A2 scenario, 2100. Weights equal to total area of each county.

PRECIPITATIONS - A2- 2090 (2080-2100 climatology with respect to 1961-1990 - % change)

	Winter									Spring								
	min	p5	p25	p50	p75	p95	max	mean	sd	min	p5	p25	p50	p75	p95	max	mean	sd
CNCM3	-39%	-22%	3%	13%	21%	34%	46%	10%	16%	-74%	-65%	-23%	-4%	9%	26%	35%	-10%	27%
CSMK3	-33%	-20%	-10%	5%	18%	27%	42%	4%	16%	-38%	-24%	-9%	5%	15%	32%	43%	3%	17%
ECHOG	-33%	-24%	-4%	5%	13%	38%	53%	5%	17%	-46%	-24%	-6%	4%	11%	21%	29%	2%	14%
GFCM20	-14%	-7%	2%	8%	14%	23%	35%	8%	9%	-67%	-59%	-30%	-1%	15%	34%	44%	-7%	28%
GFCM21	-26%	-15%	2%	13%	22%	28%	36%	11%	13%	-65%	-55%	-30%	-4%	21%	49%	62%	-5%	32%
GIER	-28%	-20%	-5%	3%	15%	29%	41%	4%	14%	-53%	-45%	-18%	16%	39%	57%	63%	10%	32%
HADCM3	-20%	-13%	1%	11%	19%	33%	47%	10%	13%	-67%	-50%	-22%	1%	22%	32%	46%	-3%	27%
INCM3	-28%	-24%	-9%	9%	25%	34%	38%	8%	19%	-24%	-20%	-13%	-5%	6%	31%	44%	-1%	15%
IPCM4	-74%	-66%	-29%	4%	32%	79%	100%	3%	43%	-59%	-51%	-31%	-15%	-1%	11%	18%	-17%	19%
MIMR	-60%	-50%	-29%	-4%	7%	23%	35%	-10%	23%	-62%	-43%	-30%	-19%	1%	18%	26%	-15%	19%
MPEH5	-24%	-4%	12%	21%	31%	45%	56%	21%	15%	-43%	-32%	-9%	5%	16%	24%	33%	2%	17%
MRCGCM	-30%	-21%	4%	17%	24%	32%	42%	13%	16%	-58%	-44%	-6%	7%	11%	25%	35%	0%	19%
NCCCSM	-46%	-24%	-9%	-3%	6%	14%	25%	-3%	11%	-54%	-36%	-1%	11%	17%	26%	36%	5%	18%
NCPCM	-27%	-11%	-4%	0%	4%	17%	21%	1%	8%	-27%	-12%	-2%	8%	14%	30%	36%	7%	12%
	Summer									Autumn								
	min	p5	p25	p50	p75	p95	max	mean	sd	min	p5	p25	p50	p75	p95	max	mean	sd
CNCM3	-57%	-42%	-23%	-7%	8%	127%	944%	8%	77%	-35%	-27%	-17%	-6%	8%	28%	531%	4%	51%
CSMK3	-46%	-23%	1%	8%	15%	51%	170%	11%	25%	-51%	-19%	0%	6%	13%	24%	45%	5%	13%
ECHOG	-91%	-76%	-14%	13%	26%	41%	3570%	45%	287%	-57%	-48%	-15%	-7%	0%	15%	53%	-9%	17%
GFCM20	-78%	-70%	-55%	-29%	-6%	106%	1861%	0%	164%	-52%	-42%	-29%	-20%	0%	29%	92%	-14%	23%
GFCM21	-74%	-66%	-53%	-40%	-27%	9%	160%	-36%	27%	-15%	-11%	-4%	6%	17%	34%	55%	8%	14%
GIER	-55%	-40%	-23%	-2%	9%	16%	45%	-6%	18%	-32%	-16%	2%	15%	24%	33%	54%	12%	15%
HADCM3	-67%	-34%	-21%	-9%	14%	93%	155%	3%	39%	-24%	-9%	10%	17%	34%	164%	619%	36%	62%
INCM3	-46%	-38%	-28%	-22%	-6%	51%	89%	-13%	25%	-23%	-20%	-17%	-13%	-6%	6%	38%	-10%	9%
IPCM4	-56%	-29%	-17%	-9%	-3%	4%	13%	-10%	10%	-63%	-45%	-20%	-8%	1%	28%	72%	-9%	21%
MIMR	-85%	-60%	-44%	-37%	-28%	9%	59%	-33%	22%	-36%	-27%	-15%	-9%	0%	18%	41%	-7%	13%
MPEH5	-59%	-21%	1%	10%	27%	69%	460%	15%	32%	-13%	-3%	7%	19%	30%	63%	133%	22%	21%
MRCGCM	-38%	-23%	0%	5%	14%	101%	279%	15%	44%	-34%	-22%	0%	12%	22%	38%	306%	15%	39%
NCCCSM	-85%	-68%	-11%	18%	29%	128%	666%	21%	84%	-41%	-26%	-13%	3%	12%	22%	37%	0%	16%
NCPCM	-59%	-47%	-15%	4%	16%	31%	55%	0%	23%	-41%	-22%	-6%	3%	14%	22%	31%	3%	13%

Table A7. Distribution of warming across all US counties that belong to our panel. A2 scenario, 2100. Weights equal to total area of each county.

Model		Institute			Scenarios			Average size of grid (degrees)		Carbon cycle model	
Acronym	Name	Acronym	Name	Country	B1	A2	A1B	Latitude	Longitude	ISAM	BERN-CC
BCCM1	CM1	BCC	Beijing Climate Center	China	X			1.9	1.9		X
BCM2	BCM2	BCCR	Bjerknes Centre for Climate Research	Norway	X		X	2.8	2.8		X
CGHR	CGCM3_1-T63	CCCMA	Canadian Centre for Climate Modelling and Analysis	Canada	X		X	2.8	2.8		
CGMR	CGCM3_1-T47	CCCMA	Canadian Centre for Climate Modelling and Analysis	Canada			X	3.7	3.8		
CNCM3	CM3	CNRM	Centre National de Recherches Météorologiques	France		X	X	2.8	2.8		X
CSMK3	MK3	CSIRO	Commonwealth Scientific and Industrial Research Organisation	Australia	X	X	X	1.9	1.9		
ECHOG	ECHO-G	CONS	Meteorological Institute of the University of Bonn	Germany		X	X	3.7	3.8		
FGOALS	FGOALS-G1_0	LASG	State Key Laboratory Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics	China	X		X	3.1	2.8		X
GFCM20	CM2	GFDL	Geophysical Fluid Dynamics Laboratory (NOAA)	USA	X	X	X	2.0	2.5	X	
GFCM21	CM2_1	GFDL	Geophysical Fluid Dynamics Laboratory (NOAA)	USA	X	X	X	2.0	2.5	X	
GIAOM	GISS-AOM	NASA	National Aeronautics and Space Administration	USA	X		X	3.0	4.0	X	
GIEH	GISS-EH	NASA	National Aeronautics and Space Administration	USA			X	4.0	5.0	X	
GIER	GISS-ER	NASA	National Aeronautics and Space Administration	USA	X	X		4.0	5.0	X	
HADCM3	HADCM3	UKMO	United Kingdom Metereological Office	UK	X	X	X	2.5	3.8		X
HADGEM	HADGEM1	UKMO	United Kingdom Metereological Office	UK			X	1.3	1.9		X
INCM3	CM3	INM	Institute of Numerical Mathematics	Russia	X	X	X	4.0	5.0		X
IPCM4	CM4	IPSL	Institut Pierre Simon Laplace	France	X	X	X	2.5	3.8		X
MIHR	MIROC3_2-HI	NIES	National Institute for Environmental Studies	Japan	X		X	1.1	1.1		X
MIMR	MIROC3_2-MED	NIES	National Institute for Environmental Studies	Japan	X	X	X	2.8	2.8		X
MPEH5	ECHAM5	MPIM	Max Planck Institute for Meteorology	Germany	X	X	X	1.9	1.9		
MRCGCM	CGCM2_3_2	MRI	Meteorological Research Institute	Japan	X	X	X	2.8	2.8	X	
NCCCSM	CCSM3	NCAR	National Center for Atmospheric Research	USA	X	X	X	1.4	1.4		X
NCPCM	PCM	NCAR	National Center for Atmospheric Research	USA		X		2.8	2.8		X

Table A8. General Circulation Models, Institutions and scenarios available.