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ABSTRACT

A growing body of economics research projects the effects of global climate change on economic outcomes. Climate scientists often criticize these articles because nearly all ignore the well-established uncertainty in future temperature and rainfall changes, and therefore appear likely to have downward biased standard errors and potentially misleading point estimates. This paper incorporates climate uncertainty into estimates of climate change impacts on U.S. agriculture. Accounting for climate uncertainty leads to a much wider range of projected impacts on agricultural profits, with the 95% confidence interval featuring drops of between 17% to 88%. An application to African agriculture yields similar results.

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1. Introduction

In recent years, leading economics and social science journals have published a growing stream of articles on the projected effects of global climate change on important economic outcomes. Such studies typically combine estimates of the historical relationship between climate variables and an outcome of interest with projections of future changes in climate, the latter typically derived from global climate models. The results of these studies have featured prominently in public policy debates, informing important decisions about appropriate investments in both greenhouse gas emissions reductions and in measures designed to help societies adapt to a changing climate. Such investments could potentially be very large: for instance, the recent US$100 billion pledged in annual transfers from rich to poor countries to help the latter adapt to expected climate impacts is close to the total annual foreign aid transfer from rich to poor countries.[1] Generating credible estimates of climate impacts is thus of considerable public policy concern.

Unfortunately, this emerging literature on the economics of climate change suffers from a major blind spot: while existing studies are typically careful to document the *statistical uncertainty* inherent in the historical relationship between climate variables and outcomes of interest, they rarely account for the large degree of *climate uncertainty* found in existing projections of climate change itself. In particular, existing studies often rely on projections from only one or a handful of climate models, despite the availability of over 20 such models that are regularly used in the climate science community, the large discrepancies across these models, and the lack of evidence that any particular subset of models is more reliable than others for long-term projections (Randall, RA Wood, et al. 2007; Meehl, TF Stocker, Collins, P Friedlingstein, AT Gaye, et al. 2007). As discussed in detail below, our survey of this growing literature reveals that of the roughly 100 papers that make quantitative climate impact projections for economic, political or social outcomes, the median number of climate models used is just two, with disproportionate dependence on only a few of the over 20 recognized models. To illustrate, many studies rely on a single model, the Hadley Centre Climate Model[2], despite the lack of systematic evidence that it is any more trustworthy than alternatives.

[1] E.g. see http://unfccc.int/resource/docs/2009/cop15/eng/l07.pdf. Total foreign aid flows in 2009 equaled roughly $120 billion (*www.oecd.org/dac/stats/data).*

[2] This includes earlier generations of the Hadley Model, now superseded by more recent modeling output. See (Gordon, C Cooper, et al. 2000b; Johns et al. 2006; Johns, RE Carnell, et al. 1997c)

As a consequence of this failure to incorporate climate uncertainty, the rapidly growing literature on the economics of climate change – while influential within economics – is unfortunately all too often disregarded outright by climate scientists, both among researchers and those advising public policymakers. From their perspective, articles published in this economics subfield seem likely to have downward biased standard errors in addition to potentially misleading point estimates, and possibly even incorrect signs.

In this article, we – a team of both social science and climate science researchers – attempt to move the economics of climate change literature forward by presenting a readily useable analytical approach that directly addresses the issue of climate uncertainty. We develop our recommended approach in the context of the influential recent literature that projects climate change impacts on U.S. agriculture, and demonstrate that accounting for climate uncertainty in estimates of climate change impacts on agricultural productivity and profits leads to a much wider range of projected impacts, as well as potentially different policy prescriptions.

In particular, we find that the variation in impact projections due to climate uncertainty is several times larger than that resulting from uncertainty in the historical relationship between climate variables (such as temperature and precipitation) and agricultural output. In fact, even with perfect knowledge of the mapping from climate to agriculture, climate uncertainty alone generates a very wide range of potential impacts: depending on the climate model and emissions scenario chosen, the projected annual losses in U.S. farm profits due to climate change could be anywhere from US$5 to 24 billion. Incorporating statistical uncertainty into these projections as well further widens the 95% confidence interval of losses to between $5 and $28 billion, or 17 to 88% of current profits.

We follow most existing studies in projecting climate change impacts under current technology and farm management practices, and do not build in the possibility of additional adaptation beyond what is implied in the historical relationships. While such adaptation could dampen projected impacts, predicting and quantifying the degree of adaptation to changing climate during 2080-2100 is inherently speculative, and as discussed below, there is surprisingly little evidence of past climate adaptation among U.S. farmers.

When we apply our methodology to outcomes in sub-Saharan Africa – a setting in which climate change impacts on agriculture impacts could have substantial impacts on livelihoods of hundreds of millions of the rural poor – we find similar results: uncertainty in climate projections represents the largest component of total uncertainty in climate impact projections, with a 95% confidence interval of estimated changes in corn yields ranging from -14% to -86%. We argue below that in other domains where precipitation changes loom larger than temperature changes, accounting for climate uncertainty could potentially change the sign as well as the magnitude of projected climate change impacts.

The structure of the remainder of the paper is as follows. Section 2 documents the use of global climate models in economics and social science research, and presents novel quantitative evidence on the widespread failure of recent studies to take climate uncertainty into account. Section 3 presents our econometric approach and quantifies the importance of accounting for climate uncertainty when estimating potential impacts on U.S. agricultural productivity. Section 4 applies our methodology to agricultural productivity in sub-Saharan Africa, and discusses some potential applications beyond agriculture. The final section concludes with specific suggestions for how climate uncertainty should be incorporated into future economics research.

2. Climate models and recent economics and social science research

2.1 The science of modeling of climate change

A basic overview of climate science models and terminology is useful before we discuss the recent economics literature on the impacts of climate change. The science of understanding past changes in climate and projecting possible future changes has evolved rapidly in recent years. The main tools for projecting future climate are coupled General Circulation Models (GCMs), which are detailed computer models that numerically approximate fundamental physical laws at time and space scales appropriate for representing global climate (Randall, RA Wood, et al. 2007). These models are "coupled" in the sense that the interaction of different components of the climate system – the ocean with the atmosphere, for example – is explicitly included in the numerical calculations. Many such models are currently in use, reflecting efforts by different research groups around the world to develop ever more refined representations of the complex physical processes that determine global climate outcomes.

There are two basic sources of uncertainty in model projections of future changes in climate: imperfect knowledge of the future trajectories of variables that might affect the climate system (most notably greenhouse gas emissions), and imperfect knowledge of how changes in these variables translate into changes in climate. The former we will refer to below as "emissions uncertainty", and the latter as "climate model uncertainty". We refer to the combination of these two sources of uncertainty as "climate uncertainty".

Emissions uncertainty is typically captured by simulating a given climate model under multiple future emissions "scenarios". To facilitate cross-model comparability, the Intergovernmental Panel on Climate Change (IPCC) developed a standardized set of these scenarios, some subset of which almost all modeling groups use as input into their modeling efforts. Known as the SRES scenarios (from the Special Report on Emissions Scenarios), these scenarios employ different assumptions about economic growth and technological change to span a range of different rates of change in anthropogenic (manmade) radiative "forcing". These scenarios provide the basis for the various climate model experiments reported in the IPCC's most recent assessment of the "state of the science", the 2007 Fourth Assessment Report, in part for which it was awarded the Nobel Prize.[3] Conditional on the use of a particular emissions scenario, "climate model uncertainty" derives from the different modeling choices climate science research groups make about how to best represent the underlying physical relationships and about which baseline conditions should be used to initialize the models.

To begin to illustrate the extent of climate uncertainty, Figure 1 presents projections of climate change in U.S. corn-growing regions between 2000 and 2080-2100, using output from 20 different climate models contributing to the IPCC's Fourth Assessment Report.[4] Climate models uniformly predict that temperatures will warm, but disagree on both the sign and magnitude of precipitation change over U.S. corn regions. Furthermore, within an emissions scenario the variation in model predictions can be large. In the oft-used A1B scenario[5], for instance, the projected mean temperature across the full ensemble of 20 models increases by 3.5 deg C (6.3 deg F), but the 95% confidence interval ranges from roughly 2C (3.6F) to 6C (10.8F). For precipitation, the ensemble mean projected change is close to zero, but individual models project

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[3] A new framework for emissions scenarios is now being used to allow exploration of a wider range of possible climate policies and more rapid response to relevant research for future IPCC assessments (Moss et al. 2010).

[4] Actual model output is compiled and made publicly available by the Coupled Model Intercomparison Project of the World Climate Research Programme (http://cmip-pcmdi.llnl.gov/). The models used in this paper are BCCR, CCCMA.t63, CCSM, CCRM, CSIRO, ECHAM, GFDL0, GFDL1, GISS.AOM, GISS.EH, GISS.ER, HADcm3, HADGEM1, IAP, INMCM3, IPSL, MIROC.Hires, MIROC.Medres, MRI, and PCM, which constitutes nearly all of the available ensemble, and the models with the appropriate combination of 20th and 21st century runs for our analysis at the time of writing. For a useful overview of available model output, refer to: http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php.

[5] The popularity of the A1B scenario is due to its assumptions of robust economic growth, moderate increases in global population, rapid adoption of technology, and "balanced" reliance on fuel sources (hence "B").

growing season precipitation rising or falling by as much as 20%. Recall that these differences across models are all driven by different assumptions made in the scientific modeling of climate rather than uncertainty about future greenhouse gas emissions. As demonstrated below for Africa, patterns of climate uncertainty found in U.S. corn-growing regions are broadly similar to those in other regions of the world.

An immediate question is how researchers should treat this wide range of climate projections. One tempting solution, and the implicit (or explicit) approach of the vast majority of the literature surveyed below, is to identify a single model or small subset of models that appear more “trustworthy”, and use only their output in impact projections. Yet this approach underestimates the uncertainty associated with long-term climate projection in at least two ways. First, in cases where only a single realization (that is, a simulation “run” from a single set of initial conditions) for a single model is used, the uncertainty arising from the inherently unpredictable (e.g., chaotic) part of climate is neglected. Second, even when multiple realizations of a single model are used, an analysis based on a single model underestimates the uncertainty associated with incomplete knowledge of all relevant physical processes that determine climate evolution. Since the climate science literature finds little evidence that particular models consistently outperform others, or that any measure of performance on past climate observations helps to narrow the future range of climate projections (Knutti 2010; Tebaldi and R Knutti 2007; Gleckler, Taylor, and Doutriaux 2008), there is no reasonable climate scientific rationale for narrowing analysis down to a single model or small number of models. In contrast to the economics of climate change literature, most studies of future climate model uncertainty carried out by climate scientists are characterized by model “democracy”. In this approach, each model that meets IPCC standards gets one “vote”, and the votes are combined into an ensemble projection whose distribution is then characterized (Meehl, TF Stocker, Collins, P Friedlingstein, AT Gaye, et al. 2007).

2.2 The existing literature on climate change impacts in economics and other social sciences

We conducted an extensive review of the climate impact literature, with particular attention to papers that use climate model information to make quantitative projections about the impacts of climate change on economic, political and social outcomes. We adopted a broad definition of “climate model”, including in our review those papers using explicit output from GCMs (the majority) as well as other papers that used quantitative climate projections of any kind, such as simple "uniform" warming scenarios of, say, a 1 deg C increase in temperature. Outcomes of interest included estimates of economy-wide or sector-specific economic damages resulting from climate change, as well as estimates of climate impacts on outcomes with clear economic consequences, such as on agricultural productivity, water resources, human morbidity and mortality, or violent conflict. We limited our search to peer-reviewed published articles as well as unpublished papers in well-known working paper series, such as the National Bureau of Economic Research and the World Bank's Policy Research series. These search criteria yielded a large number of studies. Our review is almost surely an underestimate of the total research output in this literature, but captures the most highly cited work as well as much of the recent work (over half of the papers we reviewed were published in 2007 or later).[6]

In light of climate scientists' general preference for the democratic use of climate model output, social scientists' use of climate model output is surprising. Results in Table 1 show that for the roughly 100 papers that made quantitative projections of future climate impacts, the median number of climate models used is just two. Papers on the agricultural impacts of climate change – the most developed area of study, accounting for 59% of all papers on climate impacts – do no better: the median number of climate models used is again just two. Research on climate impacts in other sectors, such as human health and water resources, show similar patterns, with studies typically relying on output from a small handful of models (Table 1).

Using only a small subset of the available climate model ensemble might be more defensible if researchers drew their subset of models at random. For instance, given the distribution of temperature projections for U.S. agriculture, simple simulations suggest that two models drawn at random will, in expectation, capture roughly 35% of the total ensemble range of temperature projections (results available upon request). However, researchers do not appear to be drawing models randomly. Despite the availability of over 20 IPCC recognized models, researchers show a strong preference for models from one particular research group, the Hadley Centre (in the United Kingdom), perhaps because their data has historically been available to researchers in a very user-friendly format. Roughly half of the studies we reviewed used Hadley models, and roughly a sixth of all the studies used *only* a Hadley model.[7]

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[6] Our review extended through December 2010, so will miss papers published since then.

[7] This again includes earlier variants of the Hadley Model, superseded by more recent output from their team.

This apparent model "non-democracy" is particularly troubling given that projections from the Hadley models do not always reflect the central tendency of the full ensemble of climate models. As Figure 1 shows for U.S. corn-growing regions, precipitation projections from the most recent coupled model from the Hadley Centre are near the ensemble mean, but its temperature projections fall outside the ensemble interquartile range. Again, the climate literature offers no evidence that the Hadley projections are overall any more (or less) trustworthy than projections from any other model, implying that the singular use of Hadley likely yields a poor representation of the range of possible outcomes. We next explore what the singular use of the Hadley model – or any other model, for that matter – implies for projections of climate impacts for U.S. agriculture.

3. An Application to U.S. agriculture

3.1 Estimating climate change impacts on agriculture

As shown in Table 1, the social science literature on climate impacts has focused disproportionately on potential impacts in the agricultural sector. This is particularly true in economics, where the most cited climate change impacts papers (discussed below) focus almost exclusively on potential damages in U.S. agriculture. Such a focus is understandable: temperature and precipitation enter directly into the agricultural production function, and while U.S. agriculture is not uniquely affected by climate, the U.S. is the world's largest exporter of agricultural goods and one of its largest overall producers.[8] The outsized effect that fluctuations in U.S. agricultural production have on global food markets thus makes potential climate impacts on U.S. agriculture a significant global public policy concern.

Despite recent advances, however, the literature on potential climate change impacts on U.S. agriculture remains unsettled. One main source of disagreement surrounds how to correctly estimate the historical relationship between weather and agricultural outcomes.[9] In a seminal paper, Mendelsohn, Nordhaus and Shaw (Mendelsohn, Nordhaus, and Shaw 1994) use a hedonic approach to relate agricultural land values in a given area to average climate in that area. If land

[8] For instance, based on the most recent (2008) data from the United Nations Food and Agricultural Organization, the U.S. is the second largest producer of cereals (behind China) and by far the largest exporter. Data available at http://faostat.fao.org.

[9] "Weather" is generally defined as the state of the atmosphere over a short period of time (e.g. days), and "climate" as longer run averages (e.g. over years or decades) of these weather realizations. Or as the old saying goes, "climate is what you expect, weather is what you get".

markets are well functioning, then the hedonic approach should capture the impact of changes in climate on agricultural production value, net of any adaptive measures that farmers can take in response to a changing climate (e.g., planting different crops or even switching to non-crop sources of income). The difficulty of this cross-sectional approach, of course, is that average climate in a given area could be correlated with many other unobserved factors (i.e., soil quality, pest populations, access to irrigation, farmer characteristics) that also affect land values, potentially biasing coefficients on climate variables in an unknown direction.

In an influential contribution, Deschenes and Greenstone (Deschenes and Greenstone 2007) (henceforth DG) propose to solve this omitted variables problem by using panel data to relate annual agricultural profits to weather realizations at the county level. Surprisingly, DG report no significant effect of weather variation on agricultural profits, and thus little potential scope for climate change to affect U.S. agricultural productivity. They estimate future climate change impacts in the 2070-2099 period by multiplying their historical weather-profit elasticities by the projected changes in climate derived from the Hadley Model. Building on DG, Fisher, Hanemann, Roberts, and Schlenker (Fisher, WM Hanemann, et al. 2010a) (henceforth FHRS) adopt DG's basic fixed-effects strategy but argue against DG's use of the historical weather data and their method for utilizing the future climate data, arguing that some seeming irregularities in the historical data bias DG toward finding no impact.[10] When these irregularities are corrected, FHRS report climate change impact projections for U.S. agriculture that are negative and both economically and statistically significant.

However, despite the important progress on econometric identification and data that they make, and in keeping with the broader economics literature on climate impacts, both DG and FHRS project impacts based on output from only one climate model, the Hadley Model. To explore the implications of climate model uncertainty in these impact projections, in this section we extend the main econometric analyses of both DG and FHRS to include climate uncertainty.

The main analytical choices to be made within this framework concern the appropriate outcome variables and the appropriate specification of the fixed effects. DG's preferred outcome

[10] In particular, FHRS show that DG's historical weather data are internally inconsistent and contain dubious values for some counties, likely a result of a coding error. With regard to climate model data, DG calculate the change in future climate as the difference between current observed climate and the modeled future climate. As discussed below, the most widely accepted method in climate science differences the *modeled* current climate and modeled future climate to obtain projected changes in climate. See Auffhammer et al (Auffhammer et al. 2011) for an excellent recent review of the appropriate use of climate data.

variable is agricultural profits, calculated as sales minus costs in a given year. The appeal of the profit measure is that, in principle, it could capture some of benefits and costs of the within-season compensatory measures farmers might undertake in response to a particular weather realization, such as altering the intensity of input use (e.g., using more irrigation water in hot years) or perhaps planting different crops or crop varieties if weather shocks are partly anticipated. In contrast, a simple crop yield measure will not account for any reallocation of resources among farm activities nor the costs associated with compensatory measures.

A downside to focusing on agricultural profits in a given season, as FHRS argue, is that farmers are able to store their harvest across seasons, accumulating stocks after a positive weather shock and drawing them down after a negative shock. If profits are calculated based on the value of sales in a given year rather than the value of production in that year (as empirically they are in DG), then this optimizing countercyclical storage behavior could attenuate the measured effects of weather on profits, and thus plausibly understate the impact of changes in climate on agricultural outcomes if farmers were to face more frequent negative shocks and were less able to use storage to smooth revenues across years. Due to these competing concerns in an area where there remains active scholarly debate, we explore climate change impacts on both corn yields and farm profits in what follows.

A second main analytical concern is how best to identify the effects of weather shocks within a fixed effects framework. DG's preferred specification uses both county fixed effects and state-by-year fixed effects, identifying the effects of weather on agriculture by comparing county specific deviations within a given state in a given year. The attraction of conditioning on state-by-year fixed effects is that the resulting parameter estimates on climate variables are less likely to suffer from omitted variables bias. The downside, as discussed by FHRS, is that temperature is typically relatively homogenous within a given state in a given year, and so including state-by-year fixed effects absorbs much of the relevant exogenous variation in the weather variables of interest. As with the choice of outcome variable, we explore results using either year- or state-by-year fixed effects, while always including county fixed effects.

3.2 Main results for U.S. agriculture

Table 2 presents estimates of the historical relationship between weather and agricultural outcomes, replicating the DG specifications, as well as using our own reconstruction of the historical weather data based on the same raw weather data as FHRS.[11] Following these two studies and a large literature in agronomy, we measure temperature in terms of "growing degree days" (GDD), which uses daily temperature in a given location to calculate the amount of time a crop is exposed to different temperature levels, which is then summed across a growing season.[12] Using DG's weather data, the estimated effects of GDD and precipitation on corn yields are significant for both the year- and state-by-year fixed effects specifications (Columns 1-2), but the coefficients are much larger using the updated historical weather data (Columns 3-4). In the profit regressions, DG's estimated effects of weather on farm profits are not statistically significantly different than zero at traditional confidence levels (Columns 5-6), but using updated weather data, both temperature and precipitation are significantly related to agricultural profits in both the year- and state-by-year specifications (Columns 7-8). FHRS draws the same conclusion, and argue that attenuation bias is likely driving the differences between their results and DG.

To derive potential climate change impacts on crop yields and profits, we follow the common approach in the literature of multiplying the coefficients obtained in Table 2 by the projected changes in these variables under climate change, as projected by the 20 different climate models displayed in Figure 1.[13] The implicit assumption in this approach is that farmers are no more able to adapt to long-run changes in climate than they are to short-run fluctuations in weather. While such an assumption might appear strong, there is surprisingly little evidence of past climate adaptation among U.S. farmers.[14]

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[11] We thank Wolfram Schlenker for sharing the historical weather data. Our regression results are nearly identical to FHRS, as they reported in an earlier working paper version of their paper, so we report only ours here.

[12] In particular, GDD on a given day is calculated as the average temperature on that day relative to a lower threshold (below which crop growth does not occur – typically 8 deg C for corn, the value used here, in DG, and FHRS) and a higher threshold (above which crop growth no longer improves – typically 32 deg C for corn). Specifically, GDD on a given data is calculated here as $\max\{\min\{Tavg_t\text{-}L,H\text{-}L\},0\}$, where $Tavg_t$ is average temperature on a given day, L the lower threshold, and H the upper threshold. GDD values for each day are then summed across the growing season.

[13] For instance, for temperature in a given location, temperature changes are calculated as climate model projected average temperature over the years 2080-2100 at that area, minus projected average temperature over the years 1980-2000 at that area. The latter are "projected" because climate model simulations typically begin much earlier in the century (e.g. 1900 or 1950), meaning observed present-day temperatures and modeled present day temperatures might not be the same. Differencing future model projected temperatures and current *observed* temperatures would thus introduce bias into estimates of temperature changes; the accepted approach is to difference future and current *modeled* temperature.

[14] To illustrate, if temperature "shocks" have the large effect on corn yields and farm profits that Table 2 suggests, one might expect that farmers would have figured out ways to adapt to these shocks over time. Similarly, if farmers do adapt to their growing environment, then one might expect crop yields in hotter regions to be less sensitive to high temperatures than crop yields in cooler regions. However, using data similar to this study, Schlenker and

Figure 2 shows the distribution of mid-century (2040-2060) and end-of-century (2080-2100) impact projections for U.S. corn yields and farm profits under three different emissions scenarios, derived by multiplying the coefficients in the relevant columns in Table 2 by the climate model projections shown in Figure 1. We ignore for the moment regression uncertainty (i.e., uncertainty in the historical relationship between climate and these outcomes, as captured in the standard errors in Table 2). Impact projections are uniformly negative, reflecting the substantial effect of high temperatures on yields and profits, and the increase in temperatures predicted by all climate models. Impact projections for end-of-century have a visibly more negative mean and increased variance relative to mid-century, reflecting the impacts of a continually warming climate but increased uncertainty about the trajectory of this warming.

Importantly, the spread in projections across models and emissions scenarios is substantial: even assuming perfect knowledge of the historical relationship between climate and agriculture, the end-of-century impact projections for the oft-used A1B emissions scenario and the year fixed effects specification suggest a decline in corn yields of between 14% and 70% (the range among the 18 climate models reporting output for the A1B scenario), and decline in agricultural profits of between 28% and 67% percent. These ranges are economically important. For instance, the coefficient-of-variation of annual U.S. corn yields over the last half-century is 26%, meaning that projections from some climate models imply future climate change impacts on corn yields will be well within historical variability, while others imply changes several times larger.

Similarly, with mean annual U.S. agricultural profits in our data of $32 billion[15], a profit decline of between 28% and 67% represents losses of between $9.0-21.5 billion annually by end-of-century relative to today. When all emissions scenarios are considered, projected annual profit losses due to climate change range from $5.3-23.5 billion by the end of century. At the

Roberts (2009) find little evidence for either of these adaptations among U.S. farmers: corn yields have not become less sensitive to temperature over time, nor are yields in the hotter U.S. South region any less sensitive to high temperatures than their northern counterparts. This could in part be because there are certain compensatory measures available to farmers in the short run – increasing irrigation application or drawing down crop stocks, for example – that are infeasible over the long run.

[15] Profits again are calculated here as reported sales minus reported expenditures. As such they will under-represents total farm income, which includes other sources of revenue such as government support.

upper end of this range, making up for these losses with government support would entail roughly a doubling of total U.S. farm support (which was at $12 billion in 2008).[16]

Projections using Hadley Model output for the A1B emissions scenario – the choice of both DG and FHRS – are highlighted as dark black vertical lines in Figure 2. As suggested above, output from this warmer-than-average model provides much more negative impact projections for both corn yields and agricultural profits than most other models, with roughly 50% larger drops in profits than the median projection across models and emissions scenarios. For the policymaker interested in the "most likely" impacts of climate, the singular use of the Hadley Model does not provide the best guide for policy.[17] More broadly, given the wide range of predictions between the best and worst case outcomes shown in Figure 2, the singular use of any one model will generally provide a poor characterization of potential outcomes.

The one exception to the pattern of extensive variability across climate models and scenarios in Figure 2 comes in the case of farm profit outcomes when the underlying regression includes state-by-year fixed effects. As discussed above, the relevant regression point estimates imply that there is little to no impact of weather on farm profits in the historical data, and this zero effect naturally compresses all estimated climate change impacts close to zero. FHRS argue that state-by-year fixed effects likely absorb much of the "good" variation in the regressors of interest, perhaps leading to the null point estimate. Importantly, though, the large standard errors in the profit specification with state-by-year fixed effects means that we cannot reject large negative effects once regression uncertainty is included in these impact estimates.

A natural next question is the importance of the climate model uncertainty presented in Figure 2 relative to the regression uncertainty stemming from imperfect knowledge of how agriculture has responded to weather historically. To quantify regression uncertainty, we bootstrap specifications in Table 2 (observations sampled 10,000 times, with replacement), fixing future climate change at the model giving the median estimated impact. As in Figure 2, we then quantify climate model uncertainty by fixing the agricultural response to weather at regression point estimates, and allowing future climate to vary across all climate models and emissions scenarios – i.e., climate uncertainty here combines both uncertainty in future emissions and in how the climate will respond to these emissions. "Total" uncertainty in impact

[16] See http://www.ers.usda.gov/briefing/farmincome/govtpaybyfarmtype.htm

[17] From a risk perspective, the tails of the distribution might also be of considerable interest, but without first looking at the distribution of model projections the analyst ex-ante has no way to know whether she is in the tail.

projections is then estimated as the combination of regression and climate uncertainty. Given the concerns with the state-by-year fixed effects specification discussed above and in FHRS, we focus on the year-fixed effects specification in what follows.

Figure 3 presents the resulting estimates of regression, climate, and total uncertainty for impacts on both corn yields and profits, based on the year-fixed effects specifications in Table 2 (columns 3 and 7). It is visually apparent that climate uncertainty swamps regression uncertainty for both agricultural outcomes and in both time periods. To quantify the relative importance of regression versus climate uncertainty, we take the ratio of the 95% confidence intervals of the climate-uncertainty-only impact projections and the regression-uncertainty-only projections. For impacts on corn yields, we estimate that climate uncertainty is 4.9 to 6.6 times as large as regression uncertainty, with a higher ratio in 2080-2100 than in 2040-2060, since emissions levels are more uncertain farther into the future. For agricultural profits, climate-related uncertainty in projected impacts is 30-57% larger than regression uncertainty. Taken together, the results in Figure 3 clearly point to the importance of climate uncertainty when estimating the projected future economic impacts of climate change.[18] The 95% confidence interval of U.S. agricultural profit losses considering both sources of uncertainty ranges from $5 to 28 billion by end of century, corresponding to drops of 17% to 88% in profits, a very wide range.

4. Beyond U.S. agriculture: An application to Africa

The comparison between climate uncertainty and regression uncertainty in U.S. agriculture is illustrative, and particularly important for economics research given the large sub-literature assessing the impacts of future climate change on U.S. agriculture. But this comparison alone does not imply that climate uncertainty always dominates regression uncertainty.

To explore the relative importance of climate versus regression uncertainty in another important setting, we extend our methodology to assess potential climate change impacts on agricultural productivity in sub-Saharan Africa (hereafter "Africa"). The importance of this

[18] In section 2.1 we described the two main sources of climate uncertainty, emissions uncertainty and model physics uncertainty, which we then combined in this analysis. Independent analysis of these terms helps clarify directions for future research in climate physics independent from economic, demographic, and technological forecasting. Individually, we find that for end-of-century profit projections, emissions uncertainty and model physics uncertainty contribute about equally to climate uncertainty: for yield projections, model physics uncertainty is about 45% larger than emissions uncertainty, likely because the yield results are driven even more by temperature increases than profits, and the across-scenario temperature differences by end-of-century are larger than with cross-model (within-scenario) differences.

extension is twofold. First, because the majority of Africans continue to depend either directly or indirectly on agriculture for their livelihoods, and are likely to for decades to come (World Bank 2008; Ravallion, Chen, and Sangraula 2007), climate impacts on agricultural productivity on the continent are of substantial policy concern. Second, African climate is influenced by different aspects of global climate (namely tropical meteorological processes and the oceans of the Southern hemisphere) and thus constitutes an independent test of climate model uncertainty from analyses of the United States.

Table 3 shows the estimated historical relationship between weather fluctuations and corn (maize) yields in Africa. Estimates are based on country-level data between 1961-2008 and regressions that include country and year fixed effects, weighting by corn area as indicated. While potential measurement error issues are much more serious in this setting – we must rely on country-level rather than county-level agricultural data, as well as monthly rather than daily weather data[19] – the similarity between the results in Africa and in the U.S. is noteworthy: corn yields are strongly negatively related to higher growing season temperatures and lower growing season precipitation, with a one degree C increase in temperature reducing yields by 10-30% depending on the specification. Unlike in the U.S., we find limited evidence for a non-linear relationship between yields and weather, and so focus on the linear specifications.

Figure 4 shows climate model projected changes in growing season temperature and precipitation over Africa for end-of-century, using the same climate models and methodology as in Figure 1. As in the U.S., there is substantial cross-model disagreement over both the magnitude of warming and the sign of precipitation change over the next century. The 95% confidence interval of changes in continental-average temperature ranges between 1.5C and 4.5C degrees, and between -5% and +10% for precipitation. Furthermore, these continental averages vastly understate the within-country variance in projections, particularly for precipitation: for

[19] In particular, we use national level agricultural yield data from the UN Food and Agricultural Organization (http://faostat.fao.org), and a gridded monthly temperature and precipitation dataset from the University of Delaware (Matsuura and Willmott 2009). Weather variables are averaged over corn (maize) growing area in each country, using crop maps from Monfreda et al (Monfreda, Ramankutty, and Foley 2008), and then temperature (precipitation) is averaged (summed) over country-specific estimates of corn growing season, using data from Lobell et al (Lobell et al. 2008). Because we only have monthly data, we cannot construct GDD estimates without further assumptions about within-month variability in temperature, and thus choose to focus on average growing season temperature and total growing season rainfall as the regressors of interest. We also do not have profit data for Africa, and so focus on the simplest available measure of productivity: yields of corn, the primary staple crop on the continent.

instance, the 95% confidence interval for changes in growing season precipitation in Niger by the end of century range between -25% and +49%.

How important is this broad range of projections for climate impact estimates on African agricultural productivity? Following Figure 3 for the U.S., Figure 5 explores the relative importance of climate uncertainty to regression uncertainty in impact projections for African corn yields, based on the area-weighted log yield specification in Table 3 (column 6). As in the U.S., median estimated impacts on corn yields by end-of-century are highly negative – we estimate average losses over the continent of more than 40% – but the confidence interval is broad, ranging from -14% to -86%. Similarly, despite somewhat noisier estimates of the historical relationship between weather and agricultural outcomes than in the U.S. (likely due to unavoidable measurement error problems when using aggregated country-level data), climate uncertainty remains as large or larger than regression uncertainty for African impact projections. For these continent-wide projections, the ratio of climate to regression uncertainty is 1.09 by end of century (Figure 5). Given that continent wide climate projections smooth some of the climate uncertainty at the country level, as noted above, these all-Africa estimates likely understate the relative importance of climate uncertainty at the country level.

The importance of climate uncertainty in climate change impacts is thus clearly not only a U.S. phenomenon. In the African context, despite generally larger regression uncertainty, climate uncertainty continues to make up the majority of overall uncertainty in climate change impact projections in African agriculture. Nevertheless, the results we present for both the U.S. and Africa are driven by the well-estimated negative historical relationship between temperature and agricultural production, and the agreement among all accepted climate models that the future climate will be warmer than the current one. In settings where historical relationships are less precisely estimated, regression uncertainty could grow in importance.

Yet there will likely be many other settings in which our results in agriculture could *under*-represent the potential importance of climate uncertainty in the distribution of possible future outcomes. We feel this is particularly likely in settings where precipitation changes are expected to drive key outcomes of interest, because over much of the world climate models disagree on both the sign and magnitude of future precipitation change (JH Christensen et al. 2007). A number of recent papers, for instance, explore the historical importance of changes in precipitation on economic and political outcomes in sub-Saharan Africa. Barrios, Bertinelli, and

Strobl (Barrios, Bertinelli, and Strobl 2010) find a robust positive relationship between precipitation and GDP growth in African countries, and conclude that declining precipitation levels across much of the African continent during the second half of the 20th century account for 15-40% of the current gap in per capita incomes between African countries and countries elsewhere in the developing world. Other papers exploring potential impacts on water and hydropower resources around the globe also demonstrate the potential importance of future precipitation changes. For example, Christensen et al (NS Christensen et al. 2004) show that persistent reductions in precipitation of just a few percentage points over parts of the American West are enough to create large shortfalls in the ability of the Colorado River to provide contracted water deliveries to the many U.S. states that depend on it. For outcomes that are sensitive to rainfall, simple extrapolation of the historical relationships could lead to large negative or large positive effects of climate change in these cases, depending on the climate model projection used. We leave the examination of these empirical cases to future research.

5. Conclusion

A rapidly growing literature examines the economic and social impacts of predicted future climate change, including an influential literature on likely climate change impacts on U.S. agriculture. We survey the existing literature and find that very few studies employ the full ensemble of approximately 20 climate change models that have undergone vigorous testing within the community of climate scientists. In fact, the median study in this literature uses just two such models, with the most influential recent studies on U.S. agriculture focusing on a single model (Hadley). As a result, most studies in the burgeoning literature on the economics of climate change do not capture the full range of plausible future climate variation, making their findings less credible among climate scientists and policymakers.

We feel that the approach presented here addresses a fundamental shortcoming in this emerging literature. This paper demonstrates that in the case of U.S. agricultural productivity, climate model uncertainty swamps regression uncertainty in magnitude, and that the results from the best case models could yield very different public policy implications than the results of the worst case models. The 95% confidence of estimated losses in U.S. agricultural profits resulting from global climate change range from -17% to -88%. We also find similar results in African agriculture.

While accounting for climate model uncertainty sometimes generates very wide confidence intervals around the estimated impacts of climate change, this greater degree of uncertainty is more defensible from the point of view of climate science. Failing to account for climate model uncertainty is analogous to reporting regression results without standard errors. Stated another way, studies that focus on a single or handful of climate models may be generating a false sense of confidence about the likely impacts of climate change, when actual future impacts are far less certain. This ability to choose among a large set of critically evaluated climate models, with their often wide range of projected temperature and precipitation changes, might also leave researchers that select just one or a few such models open to the charge of cherry picking.

We thus feel strongly that the most valid analytical approach for future social science studies on climate change impacts is the "democratic" standard we adopt in this paper, giving each IPCC model a single "vote" when carrying out the analysis, at least until that time when there is sufficient scientific consensus about the superiority of a particular model or models. Implementing the simple approach presented here should make future research on the economics of climate change both more convincing to the climate science community and also more credible to the policymakers who will depend on this research to make important public policy decisions in the years to come.

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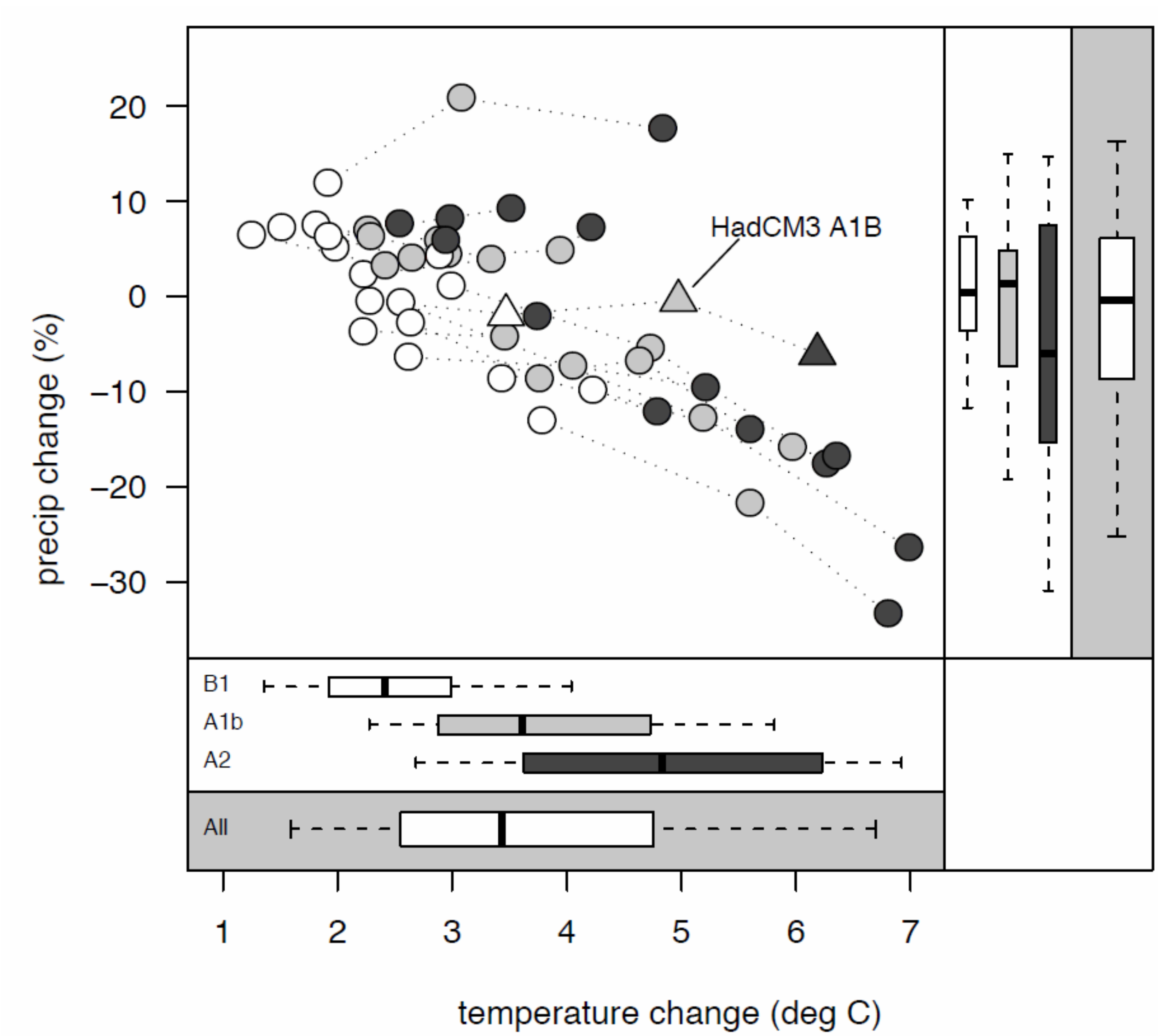

Figure 1. Projections of end-of-century (2080-2100) climate change over U.S. corn (maize) growing area, by climate model and emissions scenario. White colors represent the B1 emissions scenario, light grey colors the A1B scenario, and dark grey the A2 scenario, with projections of change in growing season temperature (in deg C) on the X-axis and percent change in precipitation (% change) on the Y-axis. Lines connect the projections for a given model across the three emissions scenarios, with projections for the Hadley model shown as triangles. Thin boxplots summarize the distribution of projected changes by scenario, and thick boxplots with the grey background summarize the combined distribution of projections across scenarios, with dark lines indicating the median projection, boxes the interquartile range, and whiskers the 95% confidence interval.

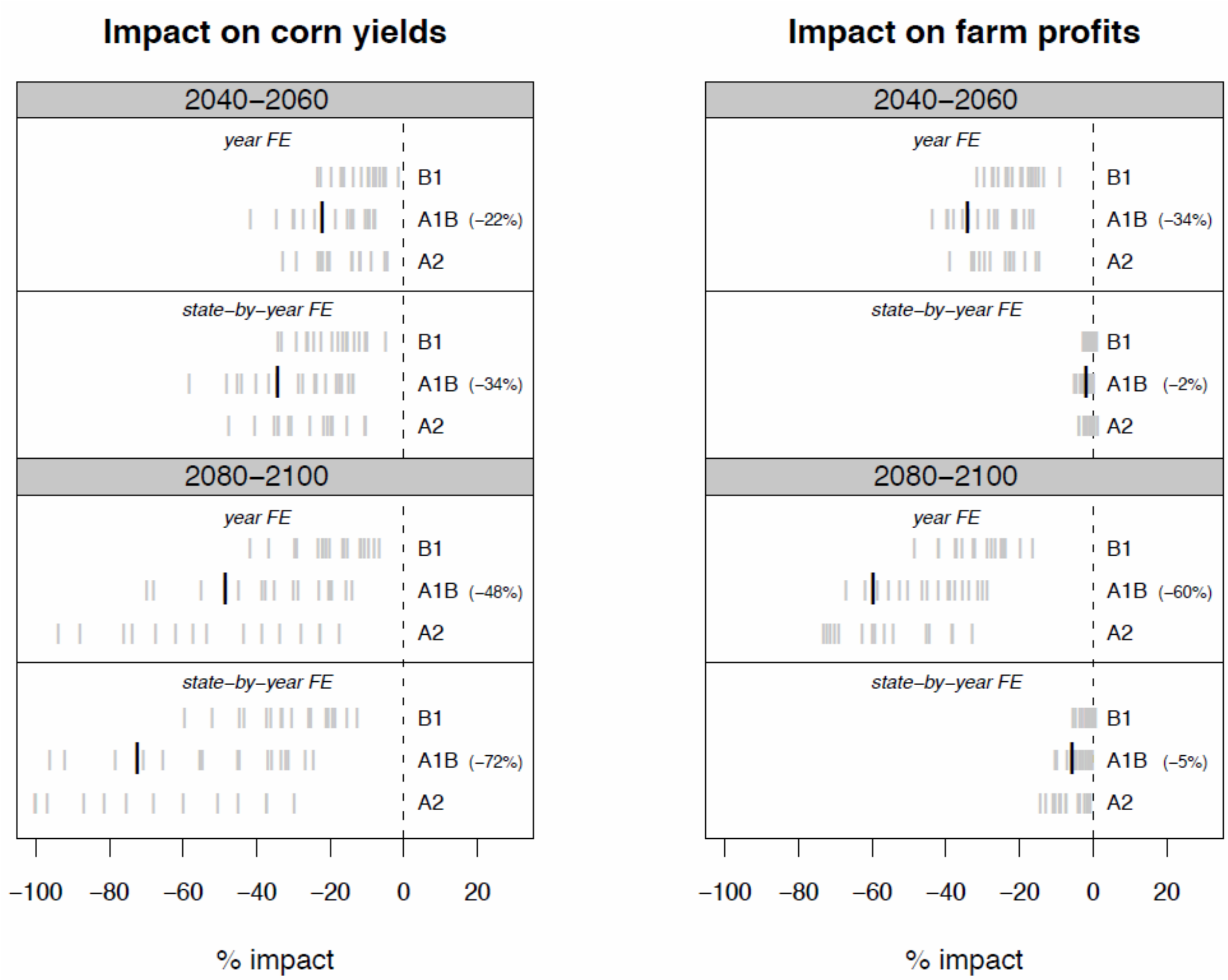

Figure 2. Projections of climate change impacts on U.S. corn (maize) yields (left figure) and farm profits (right figure) across climate models and emissions scenarios by mid-century (top panels) and end of century (bottom panels). Each grey vertical line represents projected impacts derived from a single climate model running a single emissions scenario, assuming perfect knowledge of how agricultural responds to changes in climate (that is, no regression uncertainty). Projections are based on regression specifications using either the year- or state-by-year fixed effects specifications as indicated, derived from columns 3-4 (yields) and columns 7-8 (profits) of Table 2. Dark black lines represent projected impacts from the Hadley model running the A1B scenario – the modal choice in the social science literature – with the numbers in parentheses giving the projected percentage impact for this model.

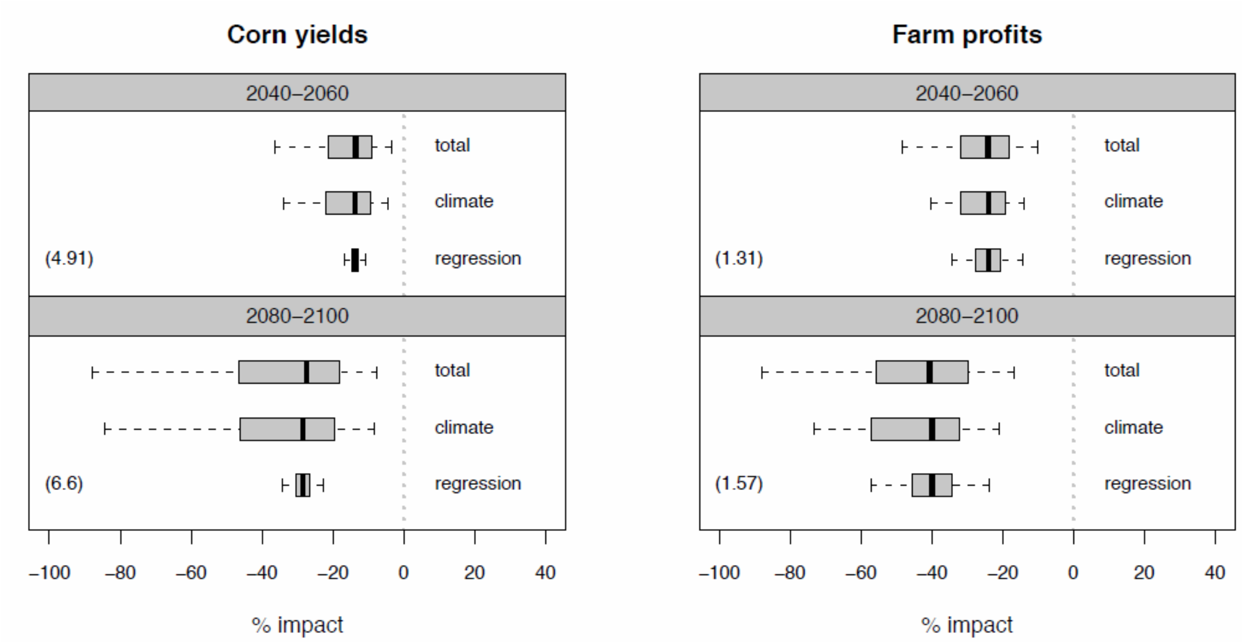

Figure 3. Importance of climate versus regression uncertainty in projections of climate impacts on U.S. corn (maize) yields (left) and farm profits (right), by mid- and end-of-century. Boxplots labeled “regression” show the uncertainty in impact projections resulting from uncertainty in the historical relationship between agriculture and climate derived from a 10,000-run bootstrap of specifications 3 and 7 in Table 2, with changes in climate fixed at the median projection. Boxplots labeled “climate” summarize projection uncertainty resulting from different emissions scenarios and model projections of how the climate will respond, with agricultural response to climate fixed at regression point estimates. Boxplots labeled “total” combine these two sources of uncertainty. Dark lines represent median projections, grey boxes the interquartile range, and whiskers the 95% confidence interval. Numbers in parentheses on the left of each panel show the ratio climate uncertainty to regression uncertainty (as calculated by the ratio of the 95% confidence intervals).

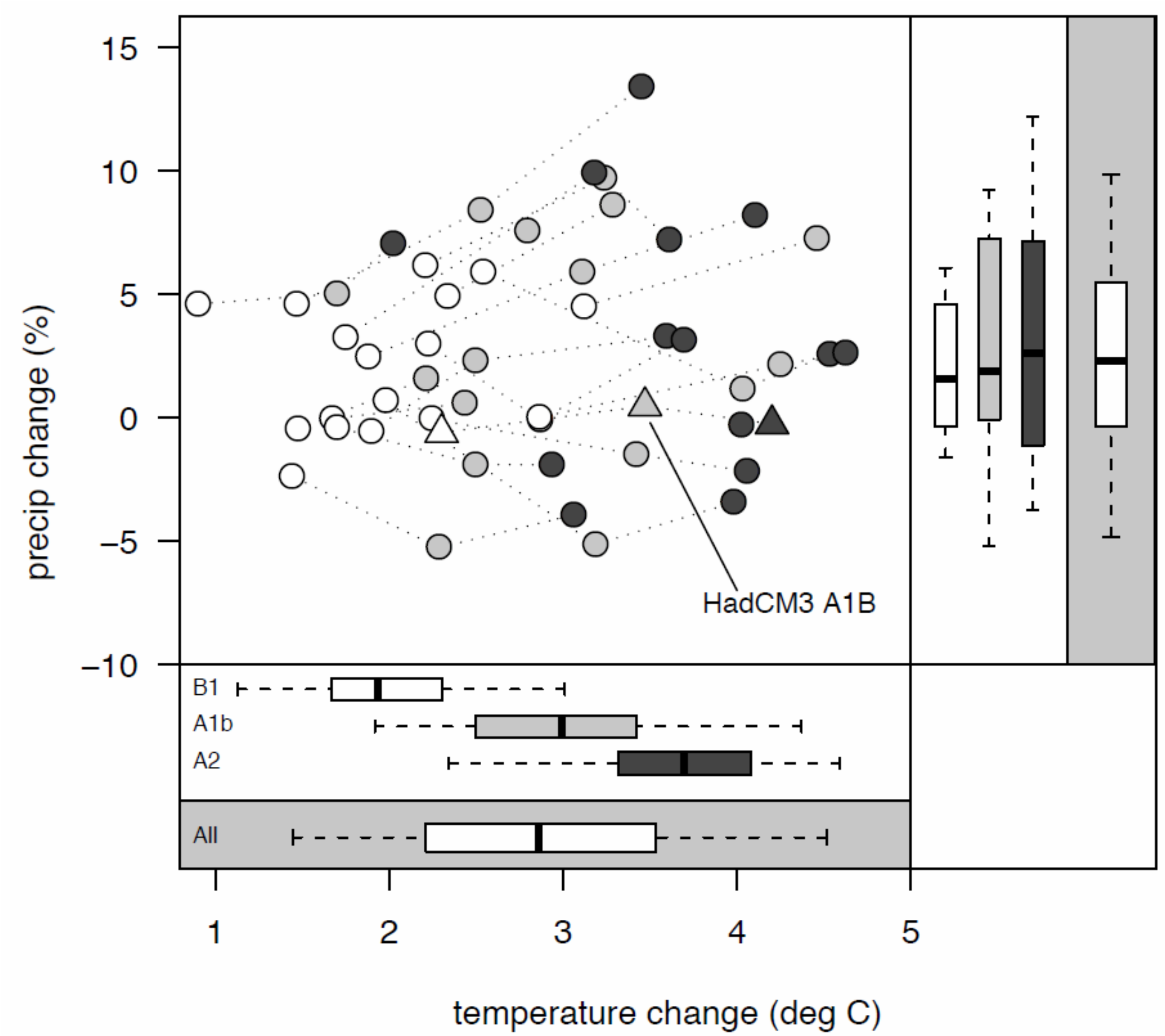

Figure 4. Projections of end-of-century (2080-2100) climate change over African corn (maize) growing area and growing season, by climate model and emissions scenario. White colors represent the B1 emissions scenario, light grey colors the A1B scenario, and dark grey the A2 scenario, with projections of change in growing season temperature (in deg C) on the X-axis and percent change in precipitation (% change) on the Y-axis. Lines connect the projections for a given model across the three emissions scenarios, with projections for the Hadley model shown as triangles. Thin boxplots summarize the distribution of projected changes by scenario, and thick boxplots with the grey background summarize the combined distribution of projections across scenarios, with dark lines indicating the median projection, boxes the interquartile range, and whiskers the 95% confidence interval.

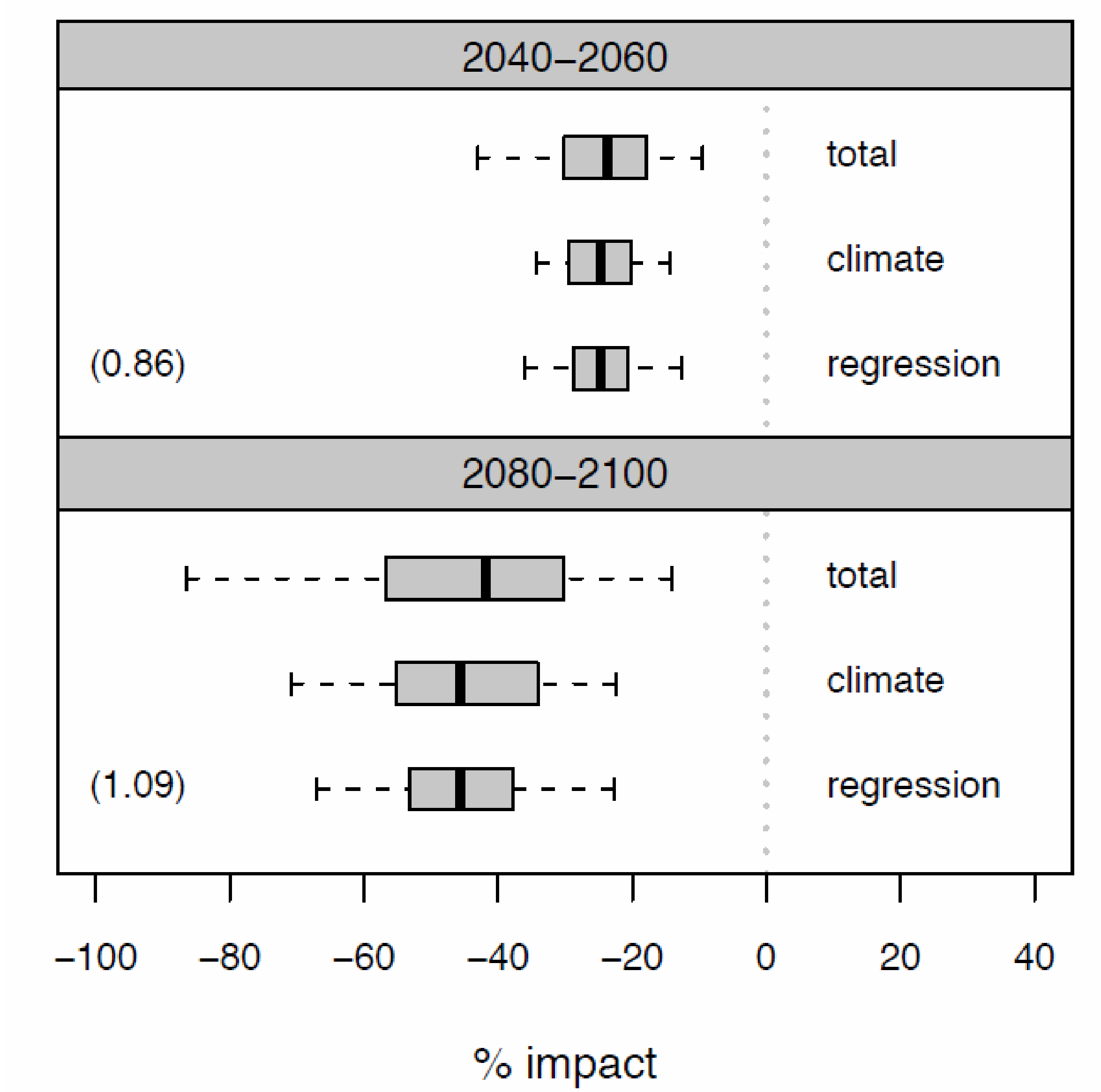

Figure 5. Importance of climate versus regression uncertainty in projections of climate impacts on African corn (maize) yields by mid- and end-of-century. Boxplots labeled "regression" show the uncertainty in impact projections resulting from uncertainty in the historical relationship between agriculture and climate derived from a 10,000-run bootstrap of column 6 in Table 3, with changes in climate fixed at the median projection. Boxplots labeled "climate" summarize projection uncertainty resulting from different emissions scenarios and model projections of how the climate will respond, with agricultural response to climate fixed at regression point estimates. Boxplots labeled "total" combine these two sources of uncertainty. Dark lines represent median projections, grey boxes the interquartile range, and whiskers the 95% confidence interval. Numbers in parentheses on the left of each panel show the ratio climate uncertainty to regression uncertainty (as calculated by the ratio of the 95% confidence intervals).

Table 1. Summary of the literature making quantitative climate change predictions about economic, political or social outcomes.

	Number of studies	Median number of climate models used	% of studies that use Hadley Model	% of studies that use only Hadley Model
Total	115	2	50	17
By sector:	*(% of total)*			
Agriculture	59	2	49	19
Health	13	1.5	92	38
Water	7	3	100	0
Multiple	13	1	31	15
Other	8	1	63	26

Note: See text for details on the criteria for inclusion in the literature survey. "Hadley Model" includes various versions of the Hadley Model.

Table 2. Effect of weather on U.S. corn (maize) yields (Models 1-4) or U.S. farm profits (Models 5-8), using various baseline data and either year or state-by-year fixed effects as indicated at the bottom. For yield regressions, Models (1) and (2) use DG baseline data, models (3) - (4) our reconstruction of the baseline climate from the PRISM data. Models (5)-(8) follow the same pattern, with profit as the dependent variable. All models include soil controls and county fixed effects. Data are from the U.S. agricultural census in the years 1987, 1992, 1997, and 2002, with "dry" referring to counties where production is mainly rainfed, and "irr" to counties where production is mainly irrigated. GDD squared coefficients have been multiplied by 10,000 to make them legible.

	(1) yield	(2) yield	(3) yield	(4) yield	(5) profit	(6) profit	(7) profit	(8) profit
GDD (dry)	0.0324***	0.0118***	0.160***	0.152***	-0.00528	0.00526	-0.0230***	0.0135
	(0.00506)	(0.00369)	(0.0109)	(0.0221)	(0.00390)	(0.00360)	(0.00856)	(0.0216)
GDD sq (dry)	-0.108***	-0.0421***	-0.490***	-0.533***	0.00582	-0.00744	-0.0115	-0.0259
	(0.0154)	(0.0118)	(0.0287)	(0.0542)	(0.0106)	(0.0101)	(0.0215)	(0.0380)
GDD (irr)	0.00903	0.0113	0.0791***	0.128***	-0.0211	-0.00663	-0.0152	0.0505
	(0.00924)	(0.00919)	(0.0237)	(0.0301)	(0.0158)	(0.0144)	(0.0275)	(0.0377)
GDD sq (irr)	-0.0222	-0.0279	-0.266***	-0.454***	0.0405	0.00619	-0.0496	-0.142*
	(0.0281)	(0.0279)	(0.0531)	(0.0700)	(0.0459)	(0.0418)	(0.0603)	(0.0778)
Precip (dry)	1.908***	1.877***	1.777***	1.258***	-0.177	0.0129	-0.392**	-0.0145
	(0.290)	(0.252)	(0.277)	(0.259)	(0.165)	(0.186)	(0.167)	(0.193)
Precip sq (dry)	-0.0109***	-0.0123***	-0.0108***	-0.00813***	0.000357	0.000514	0.00170	0.000844
	(0.00247)	(0.00211)	(0.00240)	(0.00220)	(0.00151)	(0.00170)	(0.00157)	(0.00172)
Precip (irr)	1.086***	-0.379	1.125***	-0.242	0.305	0.726	0.243	0.752
	(0.421)	(0.405)	(0.409)	(0.395)	(0.514)	(0.523)	(0.548)	(0.523)
Precip sq (irr)	-0.00551	0.00681*	-0.00757*	0.00335	-0.000587	-0.00318	-0.00144	-0.00376
	(0.00414)	(0.00384)	(0.00420)	(0.00385)	(0.00567)	(0.00576)	(0.00626)	(0.00590)
yearFE	Yes	No	Yes	No	Yes	No	Yes	No
state-by-yearFE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	6865	6865	6862	6862	9048	9048	9024	9024
Adjusted R2	0.760	0.863	0.781	0.871	0.81	0.84	0.80	0.84

Standard errors in parentheses. Models include country FE and a constant; robust errors clustered at county level
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3. Effect of weather on sub-Saharan African corn yields between 1961-2008, using either linear or quadratic weather variables and area weights as indicated at the bottom. All models include country fixed effects, year fixed effects, and a constant. See text for details on data and estimation. Robust standard errors in parentheses, clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01

	(1) levels	**(2) levels**	**(3) levels**	**(4) levels**	**(5) logs**	**(6) logs**	**(7) logs**	**(8) logs**
Temp	-0.104**	-0.376*	-0.385*	-1.013	-0.078**	-0.169**	-0.389**	-0.599
	(0.047)	(0.190)	(0.222)	(0.693)	(0.031)	(0.079)	(0.173)	(0.378)
Precip	0.201**	0.229	0.532*	0.567	0.196**	0.329**	0.645**	0.939**
	(0.099)	(0.249)	(0.266)	(0.780)	(0.097)	(0.139)	(0.244)	(0.462)
Temp sq			0.006	0.014			0.007**	0.010
			(0.004)	(0.012)			(0.004)	(0.007)
Precip sq			-0.140	-0.196			-0.190**	-0.350*
			(0.089)	(0.312)			(0.082)	(0.201)
Observations	1888	1888	1888	1888	1888	1888	1888	1888
R squared	0.19	0.42	0.20	0.42	0.15	0.34	0.16	0.35
Area weighted	no	yes	no	yes	no	yes	no	yes
F-stat weather	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00
F-stat temp	0.03	0.05	0.16	0.19	0.02	0.04	0.06	0.17
F-stat precip	0.05	0.36	0.11	0.71	0.05	0.02	0.04	0.11