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Analysis

Climate damages in the FUND model: A disaggregated analysis

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ABSTRACT

We examine the treatment of climate damages in the FUND model. By inserting software switches to turn individual features on and off, we obtain FUND's estimates for 15 categories of damages, and for components of the agricultural category. FUND, as used by the U.S. government to estimate the social cost of carbon, projects a net benefit of climate change in agriculture, offset by a slightly larger estimate of all other damages. Within agriculture there is a large benefit from CO_2 fertilization, a moderate cost from the effect of temperature on yields, and a much smaller impact of the rate of change.

In FUND's agricultural modeling, the temperature-yield equation comes close to dividing by zero for high-probability values of a Monte Carlo parameter. The range of variation of the optimal temperature exceeds physically plausible limits, with 95% confidence intervals extending to 17 °C above and below current temperatures. Moreover, FUND's agricultural estimates are calibrated to research published in 1996 or earlier.

Use of estimates from such models is arguably inappropriate for setting public policy. But as long as such models are being used in the policymaking process, an update to reflect newer research and correct modeling errors is needed before FUND's damage estimates can be relied on.

1. Introduction

The FUND model of climate economics, developed by Richard Tol and David Anthoff, is widely used, both in research and in the development of policy proposals. It was one of three models used by the U.S. government's Interagency Working Group on the Social Cost of Carbon in 2009 (Interagency Working Group on Social Cost of Carbon, 2010). The Working Group's "central estimate"[1] of the social cost of carbon (SCC), i.e. the monetary value of the incremental damages from greenhouse gas emissions, was $21 per ton of CO_2.

FUND differs from the other two models used by the Interagency Working Group, DICE and PAGE, in at least two important respects. First, it produces the lowest central estimate of the SCC, $6, compared with $30 in PAGE and $28 in DICE. (Here and throughout, SCC estimates are in 2007 dollars per ton of CO_2.) Second, FUND is far more complex than the other models, with, among other features, 15 major categories and additional subcategories of climate damages, each based on a separate analysis and estimated for each of 16 regions of the world. Many of the constants defining these damages, as well as those used in other aspects of FUND, are modeled as Monte Carlo parameters, often with means and standard deviations specified separately for each region. As a consequence of this level of detail and complexity, it seems likely that many economists and policy analysts who use FUND results are unaware of the contribution of individual features of FUND to the final outcomes.

Serious questions have been raised about the use of integrated assessment models (IAMs) of climate economics, such as FUND, in the development of public policy. IAMs apply an economic framework that is ill-suited to evaluation of intergenerational tradeoffs, and frequently ignore or minimize problems of catastrophic risk, which are central to the climate debate (Ackerman et al., 2009; Schneider, 1997). Welfare optimization models, a category that includes FUND and DICE, reopen fundamental questions, such as the optimal amount of warming to allow, offering economic judgments that may clash with well-established policy goals (Stanton et al., 2009; Stern, 2008). In general, the reliance on detailed calculation of costs and benefits, including monetization of "priceless" externalities, creates numerous problems for environmental policymaking (Ackerman and Heinzerling, 2004).

Despite such questions, IAMs, including FUND, remain important in the climate policy process, particularly in the United States. It is therefore important to understand the inner workings of the models that play a role in policy debates. This paper presents a disaggregation of the damage estimates in FUND, followed by a more detailed

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[1] "Central estimate," the Working Group's terminology, refers to the estimate of the SCC under assumptions made in the Working Group analysis, including a fixed 3% discount rate, other specified inputs, and a set of five scenarios, the results of which are averaged. Results at the 5% and 2.5% discount rates, also used by the Working Group, are qualitatively similar, and are omitted from this article to simplify the presentation.

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examination of agricultural damages. It then raises two issues about the modeling of agricultural damages in FUND, reviews recent literature relevant to agricultural damages, and recommends changes in FUND.

2. Methodology

The analysis described here begins with the Working Group's modified version of FUND.[2] Software switches were then installed, making it possible to turn off individual damage components while keeping other features of the model unchanged. FUND was then rerun with various categories turned off. Turning off a damage category X produces what might be called the "all-but-X" estimate of the SCC; the impact of X can be defined as the Working Group estimate minus the all-but-X estimate.

This can be done in either of two modes. In the Monte Carlo mode, used in the Working Group analysis and most FUND-based research, the Monte Carlo variables are all allowed to vary, and the mean outcome (typically, over 10,000 iterations) is the reported result. Alternatively, in the best-guess mode, each Monte Carlo variable is fixed at its modal value (FUND, in effect, uses "best-guess" as a synonym for modal values).[3] The contrast between Monte Carlo and best-guess results offers one readily available measure of the impact of uncertainty as modeled in FUND.

Damage calculations play two distinct roles in FUND. First, for market impact categories (i.e., excluding externality valuations), each year's damages are subtracted from the next year's output, reducing the resources available for consumption. Second, for all damage categories, the present value of the future stream of damages is the basis for the calculation of the SCC. In that calculation, the model is run twice with nearly identical patterns of emissions, differing only in an added pulse of emissions in a specific year. The SCC for that year is the present value of the difference between future damages in the two runs, per ton of carbon in the emissions pulse. The Working Group performed this calculation for several years; only the 2010 results are discussed in this paper.

3. Results

3.1. Comparing FUND and DICE

An initial experiment with FUND demonstrates that the gap between the FUND and DICE "central estimates" of the SCC can be entirely explained by the difference in their treatment of climate damages.[4] In place of FUND's disaggregated analysis, DICE uses a single equation to model damages:

$$\textit{output}\text{ net of }\textit{damages} = \textit{gross output}/\left(1+.002838T^2\right) \tag{1}$$

Gross output is the output that would have been produced in the absence of climate change, and T is the change in temperature in °C

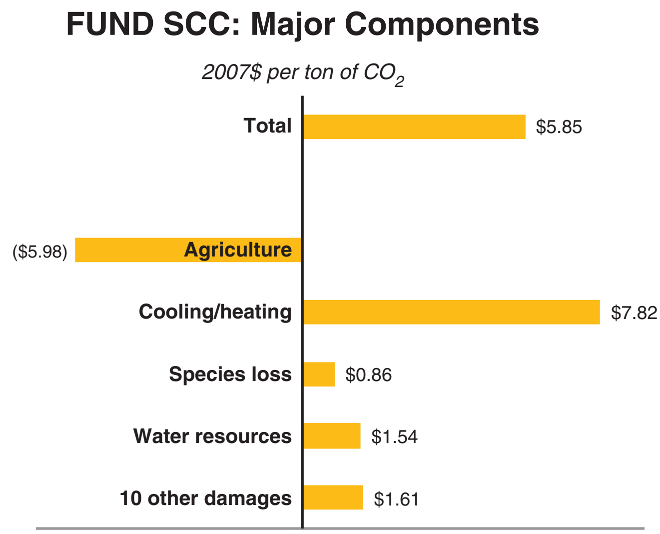

Fig. 1. FUND SCC: major components.

since 1900 (Nordhaus, 2008). When damages are calculated by substituting Eq. (1) from DICE into the Working Group version of FUND, keeping everything else unchanged, the result is an SCC of $31 per ton, about 10% greater than the DICE value. That is, if the two models agreed on DICE's climate damages, they would roughly agree in their estimates of the SCC.

3.2. Disaggregating FUND damages

FUND presents separate calculations for 15 major impact categories (of which several, including health and agriculture, include separate calculations for multiple subcategories). Two of the major categories are closely related to each other, namely the increased costs for space cooling and decreased costs for space heating, as consequences of rising average temperatures. They are combined into a single cooling/heating category in the following presentation. The cooling/heating category is always a net cost of warming, since FUND's estimate of air conditioning costs increases with temperature more rapidly than its estimate of heating costs decreases.

The agriculture and cooling/heating categories are the only large components of the FUND SCC estimate; the other 12 are quite small. Fig. 1 shows the impacts of the most important categories, when running FUND in the Monte Carlo mode used by the Interagency Working Group.

FUND's $6 SCC estimate is the sum of a $6 net benefit in agriculture, a $8 net cost in cooling and heating, and a total of $4 of net costs in the other 12 damage categories combined. The largest of the other 12 are water resources and species loss; the remaining 10 categories, including sea-level rise, storm damages, wetland losses, human health, and migration impacts, amount to a combined total of less than $2 per ton of CO_2. One of the 10 smaller categories, forestry impacts, is a very small net benefit; the others are all small net costs.

Note that the impact of cooling and heating is greater than the SCC as a whole. Thus under the Working Group assumptions, FUND estimates that all impacts of climate change, excluding the increased costs of air conditioning, would amount to a net benefit to the world.

Many or all of the categories of impacts would benefit from a review and updating. Indeed, a 2009 memorandum to US EPA evaluating the FUND model, coauthored by FUND developer Richard Tol, observed that "the model relies on literature that frequently is a

[2] Thanks to David Anthoff for providing the FUND files, and for assistance in getting FUND running on our computers. He is, of course, not responsible for any statements about FUND made in this paper.

[3] There are 73 Monte Carlo variables in FUND (listed in the FUND 3.5 data tables, available at http://www.fund-model.org/). Of these, 63 are assumed to have normal distributions — 12 unconstrained, and 51 truncated at zero (i.e. restricted to only positive, or only negative values). The remaining variables include 5 with triangular distributions, 3 with exponential distributions, and 2 with gamma distributions. For the truncated normal distributions, the mean of the underlying normal is the mode of the truncated distribution. The mode is not defined for the exponential distribution; for these 3 variables, which have small effects in practice, the "best-guess" value may be the mean.

[4] PAGE has a more complex treatment of damages than DICE, making it difficult to repeat the same experiment with the PAGE damage function.

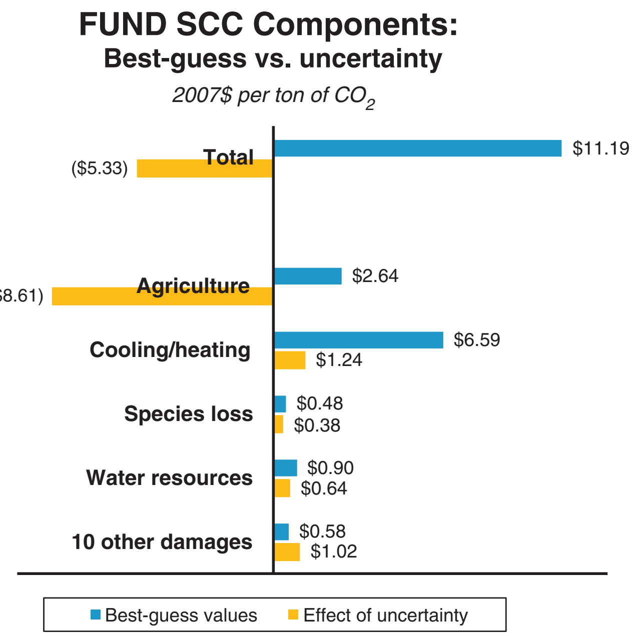

Fig. 2. FUND SCC components: best-guess vs. uncertainty.

decade old or more", and suggested hundreds of additional sources that could be consulted in an update.[5]

3.3. Best-guess values vs. effects of uncertainty

FUND also offers the option of calculation in "best-guess" mode, fixing all the Monte Carlo parameters at their modal values. Running the Working Group analysis in best-guess mode produces a SCC estimate of $11, compared with $6 in the Monte Carlo analysis. One readily available measure of the effect of uncertainty in FUND is the difference between the Monte Carlo estimates and the best-guess estimates. Using that definition of the effect of uncertainty, the estimates shown in Fig. 1 can be broken down as follows:

The sum of the two bars for each category in Fig. 2 is the value shown for that category in Fig. 1 The effect of uncertainty is positive (increases the SCC) in all cases except agriculture. Uncertainty is only a small part of the impact of cooling and heating, and about half of the impact for the 12 smaller categories. In agriculture, however, the best-guess impact is a small positive amount, or net cost, while the effect of uncertainty is a larger negative, or net benefit.

3.4. Agricultural impacts

In view of the dominant role of agricultural impacts, as seen in Figs. 1 and 2, it is worth taking a closer look at this category. FUND models agricultural impacts as the sum of three effects:

- The *CO_2 fertilization effect* assumes that agricultural production is proportional to the logarithm of CO_2 concentrations. This is always a net benefit of climate change (i.e., reduction in the SCC).
- The *optimum temperature effect* assumes that agricultural production is a quadratic function of temperature, reaching a maximum at a temperature with a most likely value somewhat above current levels. The sign of this effect can vary.

[5] "Assessment of Current FUND Modeling, by Sector," Memorandum to Stephanie Waldhoff, U.S. Environmental Protection Agency, by Joel Smith, Karen Carney, Charles Rodgers, et al., May 1, 2009. A copy is on file with the authors (confirmed to be in the public domain by personal communication from Stephanie Waldhoff, April 2011).

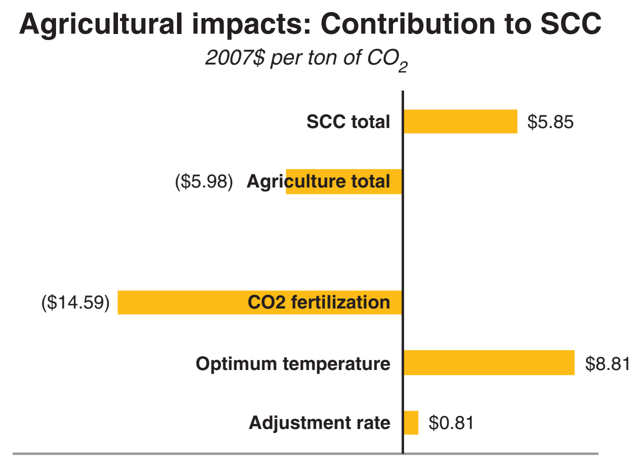

Fig. 3. Agricultural impacts: contribution to SCC.

- The *adjustment rate effect* assumes that agricultural production is decreased by adjustment costs, which are proportional to the rate of change in temperature; this is always a small net cost (increase in the SCC).

Using the same methodology, these effects can be turned off one at a time to determine their effects on the SCC. The results, corresponding to Fig. 1, are shown in Fig. 3, with the Working Group SCC and the total agricultural impact repeated from Fig. 1, for ease of comparison. The negative (beneficial) impact in agriculture is entirely due to CO_2 fertilization, which is estimated to provide a net benefit of more than $14 per ton of CO_2 emissions.

The best-guess values and the effects of uncertainty can be compared for the three agricultural subcategories,[6] as was done for the broader categories in Fig. 2. The results are presented in Fig. 4. For CO_2 fertilization, both the best-guess value and the effect of uncertainty are net benefits (reductions in the SCC); this large category drives the overall estimate of net benefits in agriculture. For the optimum temperature impact, the best-guess value and the effect of uncertainty have opposite signs — unlike the other agricultural subcategories, or the other impact categories shown in Fig. 2. The best-guess optimum temperature impact is a large net cost (increase in the SCC), while uncertainty about this impact reduces the SCC. The much smaller adjustment rate impact is essentially entirely a result of uncertainty.

4. Modeling agricultural impacts: two issues

Further examination of FUND's agricultural calculations reveals two issues that need attention; both involve the optimum temperature impact.

4.1. Risk of division by zero

The manner in which the optimum temperature effect is modeled in FUND 3.5 could cause division by zero for a plausible value of a Monte Carlo parameter. The equation for the optimum temperature

[6] In Figs. 1 and 2, the components of the SCC add up precisely to the total; in Fig. 3, the subcategories of agricultural impacts do not add up to the total for agriculture. FUND limits each region's total agricultural impacts to being no greater than the contribution of agriculture to the region's GDP. This constraint is not binding in the best-guess run, but it is in some of the Monte Carlo iterations. In the presence of this constraint, the impacts of the individual agricultural effects do not sum to the total agricultural impact. Thus the best-guess estimates for the three agricultural effects sum to the total agricultural best-guess value, but the same is not true of the Monte Carlo estimates. The difference, however, is only about $1.

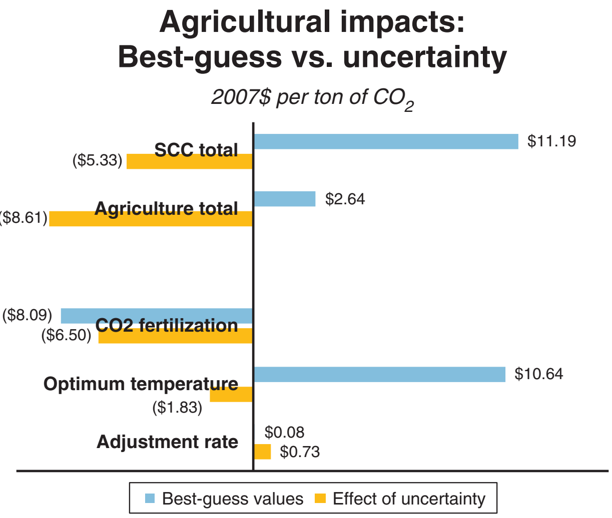

Fig. 4. Agricultural impacts: best-guess vs. uncertainty.

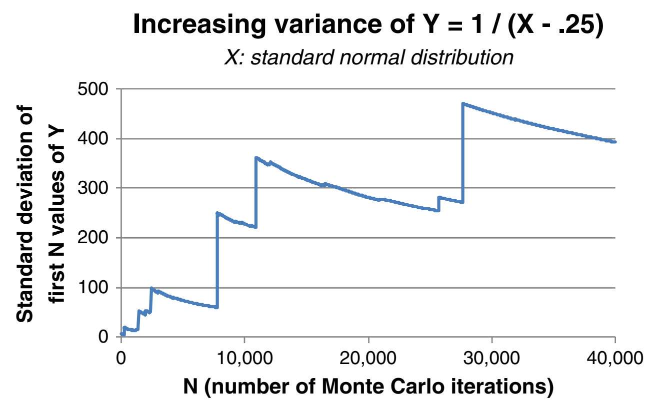

Fig. 5. Increasing variance of Y = 1/(X − 0.25).

impact, modeled as a percentage change in agricultural output, is (in slightly simplified notation):

$$Impact = \frac{-2AT^{opt}}{10.24-6.4T^{opt}}T + \frac{A}{10.24-6.4T^{opt}}T^2 \tag{2}$$

This is calculated for each time period and region. T is the average change in temperature, a global variable, and T^{opt} is the optimum temperature for agriculture. Both A and T^{opt} are Monte Carlo parameters, specified separately for each region.

In Eq. (2), the denominators of both fractions would be zero if $T^{opt} = 1.6$. This is not a problem in FUND's best-guess mode; the regional values of T^{opt} are never equal to 1.6. The closest is 1.51, and most are much farther away. In Monte Carlo mode, however, T^{opt} is a normally distributed variable; the critical value of 1.6 is within 0.25 standard deviations of the mean for every region. This implies that it will be reasonably common to draw a value very close to 1.6, making the denominator very small and the impact very big. In such cases, the magnitude of the impact will depend primarily on how close to 1.6 the value of T^{opt} turns out to be. Ironically, this problem could become more severe as the number of Monte Carlo iterations rises, since the likelihood of coming dangerously close to the critical value steadily increases. (In the Working Group analysis, there are 10,000 iterations, each involving selection of 16 values of T^{opt}, one for each region.)

The problem is generic to formulations such as (2). If X is a non-negative random variable with a probability density function f that is positive at zero (i.e., $f(0) > 0$), then $Y = 1/X$ has a "fat tailed" probability of arbitrarily large values: for sufficiently large r, the probability $p(Y > r) = p(X < 1/r) \approx (1/r)f(0)$. In formal mathematical terms, Y is regularly varying with tail index 1; that is, the tail of Y is decreasing at a polynomial rate of degree −1. Whether the mean of Y exists depends on the distribution of X, but in any case, the expected value $E(Y^a)$ is infinite for $a > 1$. In particular, the variance of Y is infinite.

The same problem arises, of course, for the function $Y = 1/(X - c)$, if there is a positive probability of the value $X = c$. Consider a numerical example, where X has a standard normal distribution (mean 0, standard deviation 1), and $c = 0.25$. Using Excel, we drew repeated values of X, and calculated $Y = 1/(X - 0.25)$. The standard deviation of Y, for sample sizes up to 40,000, is shown in Fig. 5. The standard deviation of Y quickly becomes orders of magnitude greater than the standard deviation of X, and continues to grow. We discontinued our numerical simulation when, after about 42,000 iterations, the Excel random number generator drew a value of $X = 0.24999902$, leading to Y greater than 1,000,000 in absolute value, and increasing the standard deviation of Y by another order of magnitude. That is exactly the problem: the larger the sample, the greater the danger of drawing values of X so close to c that Y becomes meaninglessly large (in absolute value).

Both coefficients in Eq. (2) have structures comparable to Y in this example (after linear transformation of variables): the denominator is a normally distributed random variable, minus a constant that is within 0.25 standard deviation of the mean of the random variable. Thus the variance of each coefficient will increase without limit as the number of Monte Carlo iterations increases, and (2) will provide an increasingly unreliable estimate of agricultural impacts.

Two simple ways of removing the problem would imply similar changes in the estimate of the SCC. (These changes are introduced solely to explore the sensitivity of FUND outputs to the structure of Eq. (2), not as recommendations for a corrected model structure; the authors of FUND have, quite reasonably, responded that this simple tinkering with one equation is not an appropriate way to revise the model.[7]) First, FUND can be run with T^{opt} fixed at its best-guess value for each region; that is, Eq. (2) is unchanged, but T^{opt} is no longer a Monte Carlo parameter.[8] Everything else about the model, including the definition of A in Eq. (2) as a Monte Carlo parameter, is also unchanged. This change has no effect on the best-guess value, but increases the Working Group's central estimate of the SCC by more than $10, from $5.85 to $16.21.

Alternatively, Eq. (2) can be modified to use the global average value of T^{opt}, roughly 1.28, in the denominator of both fractions. The denominator becomes equal to 2.056, so the equation becomes

$$Impact = \frac{-2AT^{opt}}{2.056}T + \frac{A}{2.056}T^2 \tag{3}$$

In this variant, both A and T^{opt} are still Monte Carlo parameters, but T^{opt} no longer appears in the denominator. This change alone increases the best-guess value of the SCC only slightly, from $11.19 (as shown in Fig. 2) to $11.68. The Monte Carlo estimate, corresponding to the Working Group's $5.85, becomes $17.98, or an increase of $12.

Thus two different ways of eliminating the problem in the optimum temperature equation, making no other changes, would raise the FUND estimate of the SCC by $10–$12. This result suggests that the FUND estimate of the SCC is significantly affected by the Monte Carlo iterations in which T^{opt} is dangerously close to the critical value of 1.6.

A fix for the optimum temperature equation bug is planned for the next version of FUND.[9] The anomaly is unfortunately present, however,

[7] Personal communication, David Anthoff, December 2010.
[8] We implemented this change by setting the standard deviation of T^{opt} to zero for every region in the FUND data file.
[9] Personal communication, David Anthoff, December 2010.

in the versions that have been used in the past, including version 3.5, which was used for the Working Group's calculation of the SCC. In FUND versions 2.8 and 3.3, the earlier versions for which documentation is available on-line, the optimum temperature impact is defined by an equation with the same structure as (2), but with the denominators of the two fractions equal to ($1–2T^{opt}$). Thus the critical value that would cause a zero denominator was $T^{opt} = 0.5$ in FUND version 3.3 and earlier.

4.2. Implausible temperature ranges

In addition to the potential problem of near-zero denominators, the optimum temperature equation employs an extremely wide range of variation in its Monte Carlo analysis. Table 1 presents data, from the FUND 3.5 data tables, on optimal temperature increases for the model's 16 regions of the world: the means and standard deviations of the normal distributions used in the Monte Carlo analysis, and a calculation of the 95% confidence intervals (the mean plus or minus 1.96 standard deviations). The means are smaller than the standard deviations in every case, much smaller in most cases; if this is the best information available about optimum temperatures, one could argue that they may not be significantly different from zero. (The same could be said, for the same reason, of the agricultural adjustment rate effect parameter; but as seen in Figs. 3 and 4, the adjustment rate effect is close to zero in any case.)

The width of the confidence intervals in Table 1 appears to exceed physically plausible temperature ranges for agriculture. FUND asserts 95% confidence that the optimal temperature for agriculture in South America, for instance, is between 17 °C below and almost 18 °C above 1990 levels; the intervals for Canada, and for Australia and New Zealand, are almost equally extreme. For the United States, the corresponding range is from −7 °C to +9 °C. The upper end of the 95% confidence interval is more than 5 °C above 1990 temperatures everywhere. In five regions, it is more than 10 °C above 1990; at that global average temperature, many parts of the world would be too hot for human beings to survive (Sherwood and Huber, 2010). The lower end of the confidence interval is more than 5 °C below 1990 temperatures – that is, at or below the temperature of the last ice age – in eight regions.

Monte Carlo analysis across these intervals – including the even higher "optimum temperatures" that will be chosen for each region in 250 of the 10,000 iterations – would seem to be exploring hypotheses about the state of the world that could safely be ruled out in advance. In each Monte Carlo iteration that selects a very high optimum temperature, FUND calculates a double benefit from climate change: both the fertilization from increasing CO_2 concentrations, and the increasing (but still sub-optimal) temperature, are estimated to have separate, positive effects on agriculture. Since FUND has a lower bound on agricultural damages (see footnote 6), but no upper bound on agricultural benefits, Monte Carlo analysis across an excessively wide range of possibilities increases the reported average agricultural benefits.

Table 1
Optimal temperature for agriculture in FUND 3.5. (Measured in °C above 1990).

	Mean (μ)	Standard deviation (σ)	95% confidence interval	
			μ − 1.96σ	μ + 1.96σ
USA	1.09	4.14	−7.02	9.20
CAN	2.92	7.64	−12.05	17.89
WEU	0.79	3.29	−5.66	7.24
JPK	0.98	6.61	−11.98	13.94
ANZ	2.00	8.00	−13.68	17.68
EEU	1.31	2.73	−4.04	6.66
FSU	1.46	2.44	−3.32	6.24
MDE	1.32	2.03	−2.66	5.30
CAM	1.05	3.60	−6.01	8.11
SAM	0.35	8.82	−16.94	17.64
SAS	1.13	2.41	−3.59	5.85
SEA	0.70	5.12	−9.34	10.74
CHI	1.43	2.49	−3.45	6.31
NAF	1.20	2.74	−4.17	6.57
SSA	1.22	2.76	−4.19	6.63
SIS	1.51	2.92	−4.21	7.23

5. Implications: the need for updated agricultural estimates

Since the FUND model remains important in the ongoing discussion of climate policy, there is a need to update and improve its damage estimates. In the area of agricultural impacts, the technical description for FUND 3.5, written in 2010, states that the model's estimates are calibrated to research results published in 1992–1996. There has been a substantial advance in the understanding of agriculture and climate change since 1996, which might lead to different estimates.

Early studies of carbon fertilization, usually done in greenhouses, suggested that it would lead to very large gains in agricultural yields. Recently, however, more realistic outdoor experiments have suggested that the benefits will be much smaller, perhaps half the size of the earlier estimates (Leakey et al., 2009; Long et al., 2006). A recent economic analysis of agriculture and climate change concluded that an increase in atmospheric concentration to 550 ppm of CO_2 would, on average, increase agricultural yields by 9% (Cline, 2007).

When a simple carbon fertilization relationship is assumed to apply to all future CO_2 concentrations, there is a risk of out-of-sample forecasting: as concentrations rise, in high-emission climate scenarios, do yields keep rising forever? An unbounded logarithmic relationship between CO_2 concentrations and yields, as assumed in FUND, means that each doubling of CO_2 concentrations produces the same increase in agricultural output. Yet there is very little empirical information available about yields at higher concentrations.

A more cautious modeling approach might assume moderate yield gains, along the lines of Cline (2007), for the initial increases in CO_2 concentration, but little or no further gains thereafter. This would reduce the large net benefits which FUND currently estimates from CO_2 fertilization, particularly in high emission, business-as-usual scenarios.

The optimum temperature effect, as modeled in FUND, makes agricultural output a quadratic function of temperature (see Eq. (2)); even with the simplest fixes for the division-by-zero problem, as proposed in the last section, the relationship is still quadratic. This implies perfect symmetry between the impacts of higher- and lower-than-ideal temperatures: with a quadratic relationship, the projected yield is necessarily the same at 1° above and 1° below the optimum. Again, recent research suggests a different pattern.

In a detailed empirical study of the effects of temperature on U.S. corn, soybeans, and cotton yields, Schlenker and Roberts (2009) found very slow, small increases in yields on the way up to an optimum temperature (which was 29 °C for corn, 30 °C for soybeans, and 32 °C for cotton), followed by rapid declines in yields above the optimum. For corn, replacing 24 hours of the growing season at 29 °C with 24 hours at 40 °C causes a predicted yield decline of about 7%.

Their results do not at all resemble a quadratic relationship; a closer approximation would be a horizontal line (constant yield) up to the optimum temperature, followed by a steep drop-off in yield at higher temperatures. This would require a different functional form for the optimum temperature effect, in place of Eq. (2). Schlenker and Roberts find no evidence of successful adaptation, such as development of heat-resistant crop varieties, in parts of the United States which have long been above the optimum temperatures for much of the growing season.

Corn, soybeans, and cotton are three of the world's highest-value crops, and the United States produces a significant fraction of global supply, including 41% of corn and 38% of soybeans (Schlenker and Roberts, 2009). Thus this is not just a case study, but a description of a large part of world agricultural production. Use of the Schlenker and Roberts curves, in place of FUND's current quadratic relationship between yield and temperature, would have a major effect on the estimates of agricultural impacts of climate change: it would reduce the large estimated gains from warming, particularly in the Monte Carlo iterations where FUND currently picks very high optimum temperatures.

6. Conclusions

One conclusion from this discussion is that, as we noted at the outset, questions could be raised about the use of models such as FUND in setting public policy. Yet as long as such models remain in use, model results matter. The estimate of the SCC adopted by U.S. government agencies, for use in calculations such as cost-benefit analyses of proposed regulations, is based on the results of three models of climate economics — of which FUND is the most complex and least understood. Models that play such a prominent role need to be transparent, widely understood, and up to date and consistent with the latest empirical research.

This paper has introduced a software innovation that increases the transparency of the FUND model: switches that allow individual damage categories to be turned on and off, in order to understand their relative contributions to the final results. FUND's $6 SCC estimate, lower than some other models, is the sum of an estimated net benefit in agriculture, a net cost in heating and cooling, and very small net costs in all other areas.

All of the damage categories in FUND should be examined and updated; some widely discussed climate impacts, such as sea-level rise and extreme weather events, are estimated to add almost nothing to the SCC in FUND. While this could be a surprising and important result about the magnitude of the empirical evidence, it could also be an indication that FUND's impact estimates are in need of revision.[10]

In the area of agriculture, FUND currently relies on research from 1996 or earlier to estimate a large net benefit from CO_2 fertilization, an optimum temperature effect on yields, and a small effect from the rate of temperature change. The first two, which account for virtually the entire agricultural estimate, are both in need of revision. Newer research suggests smaller benefits from CO_2 fertilization, and says nothing about whether these benefits continue at very high concentrations. A flaw in FUND's optimum temperature equation needs to be fixed, to prevent the risk of division by zero; and the quadratic shape of that equation is inconsistent with recent research on temperature and yields.

Since model results matter, so do the damage calculations used inside the models. The two quick fixes to the division-by-zero problem described in Section 4.1 would raise the FUND estimate of the SCC from $6 to $16–$18, a substantial change that highlights the importance of this problem. This is not to say that either of those quick fixes would produce the right estimate of the SCC. Nonetheless, the problems identified here require attention. Much more careful work, including examination of damage categories beyond agriculture, should be done to produce a thorough revision of FUND.

We have demonstrated that problems in model specification and methodology, and failure to update the empirical evidence used in the model, can have relatively large effects on the results. The fact remains that model estimates are being treated as establishing a precise SCC value that can be used in policy analysis. Therefore it is essential to revisit those estimates, and the assumptions and inputs behind them, starting now, and continuing on a regular basis.

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[10] For a recent review of new developments in climate science and economics that should inform models such as FUND, see Ackerman and Stanton (2011).