

SUMMARY OF MAJOR POINTS

Patrick J. Michaels
Center for the Study of Science
Cato Institute

1. The equilibrium climate sensitivity (ECS) in the existing federal determination of the social cost of carbon is outdated and does not reflect multiple findings in recent years that the mean ECS is significantly lower, by approximately 40%, than the value used by the Obama Administration.
2. The probability distribution for the ECS in the existing federal determination of the social cost of carbon is outdated and does not reflect multiple findings in recent years that dramatically reduce the probability of an ECS of $>3.5^{\circ}\text{C}$.
3. Satellite and balloon-sensed bulk atmospheric temperatures have warmed about half as much as was forecast since 1979 when the satellites became operational. New calculations of the social cost of carbon should take this into account.
4. Either the period 1979-present will be the most unusual period of anthropogenerated warming, or the IPCC mean ECS figure is between 50 to 33 per cent too large. New calculations of the social cost of carbon must take this into account.
5. There is an upward spike at the end of these records owing to the very strong 2015-6 El Niño that surface data show has recently dropped near to its pre- El Niño level.
6. The largest predicted warming is above the surface in the tropical atmosphere. In reality, temperatures have warmed less than half of the forecast value.
7. This error in the vertical dimension means that all model calculations of tropical rainfall changes have negative utility, and mis-specifying the vertical changes in temperature largely invalidate any forecasts of persistent changes in weather regimes.
8. The existing SCC calculations largely ignore the magnitude, or even the existence of the highly documented (and observed) enhancement of plant growth caused by increasing atmospheric carbon dioxide.
9. Satellite data confirm that the earth's surface is becoming greener, with the largest changes being on the margins of the world's great deserts. There is no accounting for this in the current calculation of the SCC.

WRITTEN STATEMENT OF

PATRICK J. MICHAELS

DIRECTOR
CENTER FOR THE STUDY OF SCIENCE
CATO INSTITUTE
WASHINGTON, DC

HEARING ON

AT WHAT COST? EXAMINING THE SOCIAL COST OF CARBON

BEFORE THE
U.S. HOUSE OF REPRESENTATIVES
COMMITTEE ON SCIENCE, SPACE, AND TECHNOLOGY
SUBCOMMITTEE ON ENVIRONMENT
SUBCOMMITTEE ON OVERSIGHT

FEBRUARY 28, 2017

Patrick J. Michaels is the director of the Center for the Study of Science at the Cato Institute. Michaels is a past president of the American Association of State Climatologists and was program chair for the Committee on Applied Climatology of the American Meteorological Society. He was a research professor of Environmental Sciences at University of Virginia for 30 years, and Virginia State Climatologist for 27 years. Michaels was a contributing author and is a reviewer of the United Nations Intergovernmental Panel on Climate Change, which was awarded the Nobel Peace Prize in 2007.

His writing has been published in the major scientific journals such as *Geophysical Research Letters*, *Journal of Geophysics*, *Climatic Change*, *Nature* and *Science* as well as popular serials worldwide. He is the author or editor of seven books on climate and its impact, and he was an author of the climate “paper of the year” awarded by the Association of American Geographers in 2004. He has appeared on most of the worldwide major media.

Michaels holds AB and SM degrees in biological sciences and plant ecology from the University of Chicago, and he received a PhD in ecological climatology from the University of Wisconsin at Madison in 1979.

I am Patrick J. Michaels, Director of the Center for the Study of Science at the Cato Institute, a nonprofit, non-partisan public policy research institute located here in Washington DC, and Cato is my sole source of employment income. Before I begin my testimony, I would like to make clear that my comments are solely my own and do not represent any official position of the Cato Institute.

My testimony concerns the selective science that underlies the existing federal determination of the Social Cost of Carbon and how a more inclusive and considered process would have resulted in a lower value for the social cost of carbon.

Back in 2015, the federal government's Interagency Working Group (IWG) on the Social Cost of Carbon released a report that was a response to public comments of the IWG's determination of the social cost of carbon that were solicited by the Office of Management and Budget in November 2013. Of the 140 unique sets of substantive comments received (including a set of my own), the IWG adopted none. And apart from some minor updates to its discussion on uncertainty, the IWG, in its most recent August 2016 report, retained the same, now obsolete, methodologies that were used in its initial 2010 SCC determination.

Here, I address why this decision was based on a set of flimsy, internally inconsistent excuses and amounts to a continuation of the IWG's exclusion of the most relevant science—an exclusion which assures that low, or even negative values of the social cost of carbon (which would imply a net benefit of increased atmospheric carbon dioxide levels), do not find their way into cost/benefit analyses of proposed federal actions. If, in fact, the social cost of carbon were near zero, it would eliminate the justification for any federal action (greenhouse gas emissions regulations, ethanol mandates, miles per gallon standards, solar/wind subsidies, DoE efficiency regulations, etc.) geared towards reducing carbon dioxide emissions.

Equilibrium Climate Sensitivity

In May 2013, the Interagency Working Group produced an updated SCC value by incorporating revisions to the underlying three Integrated Assessment Models (IAMs) used by the IWG in its initial 2010 SCC determination. But, at that time, the IWG did *not* update the equilibrium climate sensitivity (ECS) employed in the IAMs. This was not done, despite, now, there having been, since January 1, 2011, at least 16 new studies and 32 experiments (involving more than 50 researchers) examining the ECS, each lowering the best estimate and tightening the error distribution about that estimate. Instead, the IWG wrote in its 2013 report: "It does not revisit other interagency modeling decisions (e.g., with regard to the discount rate, reference case socioeconomic and emission scenarios, or equilibrium climate sensitivity)."

This decision was reaffirmed by the IWG in July 2015 and again in its most recent August 2016 report. But, through its reaffirmation, the IWG has again refused to give credence to and recognize the importance of what is now becoming mainstream science—that the most likely value of the equilibrium climate sensitivity is lower than that used by the IWG and that the estimate is much better constrained. This situation has profound implications for the determination of the SCC and yet continues to be summarily dismissed by the IWG.

The earth’s equilibrium climate sensitivity is defined by the IWG in its 2010 report (hereafter, IWG2010) as “the long-term increase in the annual global-average surface temperature from a doubling of atmospheric CO₂ concentration relative to pre-industrial levels (or stabilization at a concentration of approximately 550 parts per million (ppm))” and is recognized as “a key input parameter” for the integrated assessment models used to determine the social cost of carbon.

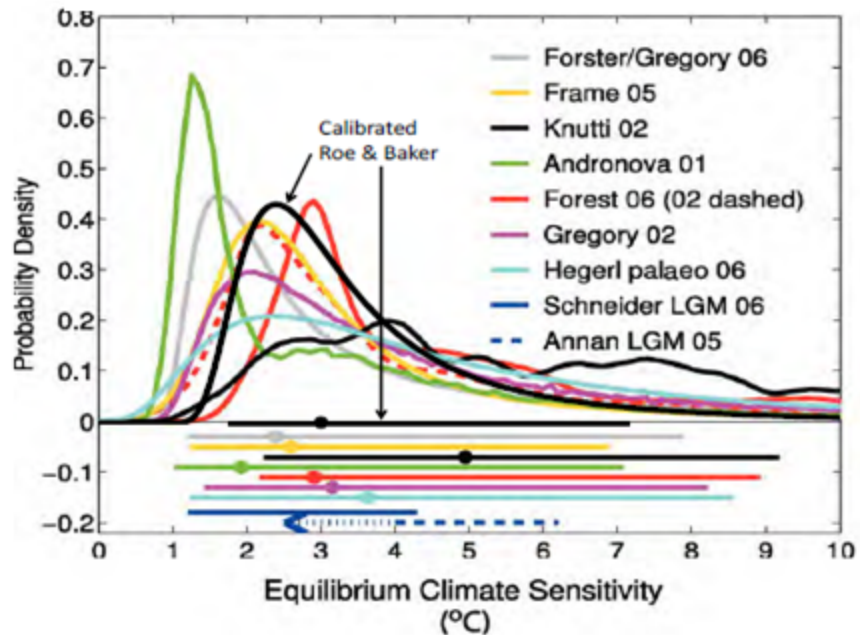
The IWG2010 report has an entire section (Section III.D) dedicated to describing how an estimate of the equilibrium climate sensitivity and the scientific uncertainties surrounding its actual value are developed and incorporated in the IWG’s analysis. The IWG2010, in fact, developed its own probability density function (pdf) for the ECS and used it in each of the three IAMs, superseding the ECS pdfs used by the original IAMs developers. The IWG’s intent was to develop an ECS pdf which most closely matched the description of the ECS as given in the *Fourth Assessment Report* of the United Nation’s Intergovernmental panel on Climate Change which was published in 2007.

The functional form adopted by the IWG2010 was a calibrated version of the Roe and Baker (2007) distribution. It was described in the IWG2010 report in the following Table and Figure (from the IWG2010 report):

Table 1: Summary Statistics for Four Calibrated Climate Sensitivity Distributions

	Roe & Baker	Log-normal	Gamma	Weibull
Pr(ECS < 1.5°C)	0.013	0.050	0.070	0.102
Pr(2°C < ECS < 4.5°C)	0.667	0.667	0.667	0.667
5 th percentile	1.72	1.49	1.37	1.13
10 th percentile	1.91	1.74	1.65	1.48
Mode	2.34	2.52	2.65	2.90
Median (50 th percentile)	3.00	3.00	3.00	3.00
Mean	3.50	3.28	3.19	3.07
90 th percentile	5.86	5.14	4.93	4.69
95 th percentile	7.14	5.97	5.59	5.17

Some previous estimates of the Probability Density Function for the Equilibrium Climate Sensitivity, including the calibrated Roe and Baker distribution

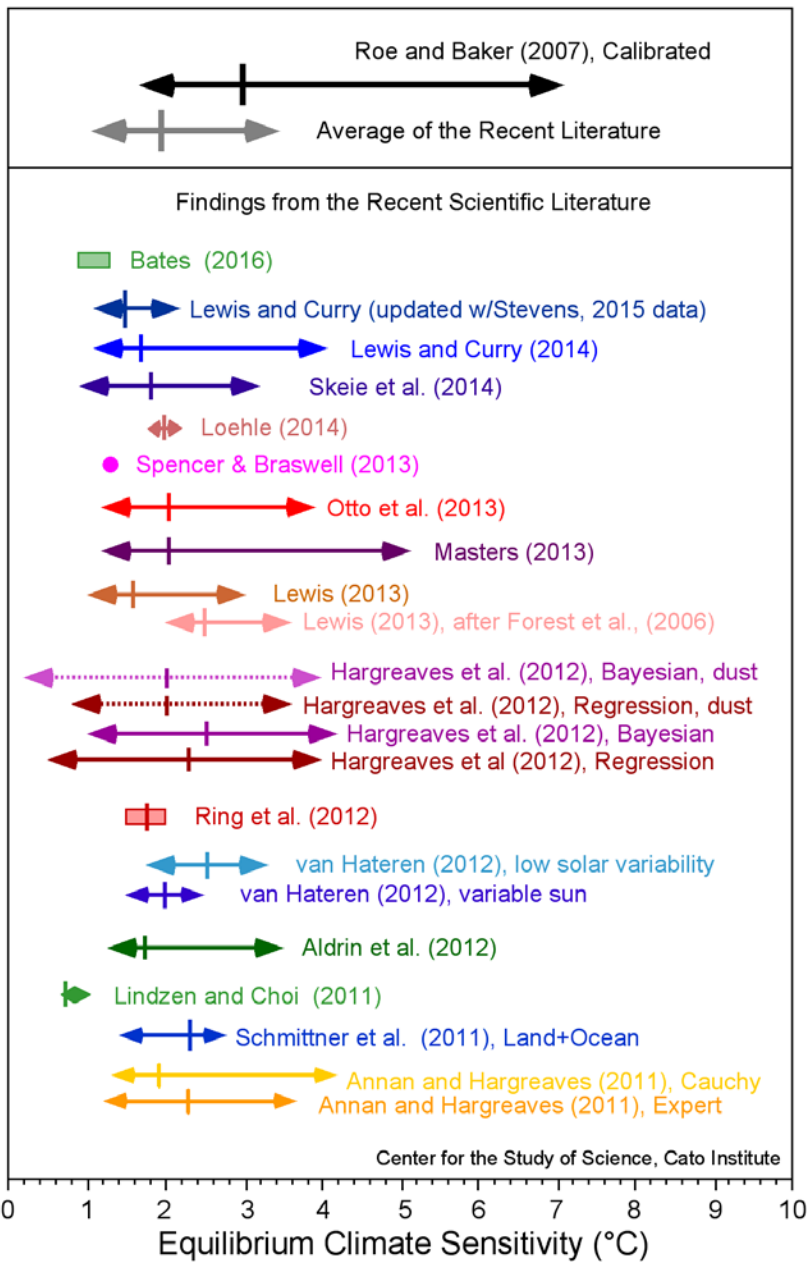


The calibrated Roe and Baker functional form used by the IWG2010 is *no longer scientifically defensible*; nor was it at the time of the publication of the IWG 2013 SCC update, nor at the time of the August 2016 update.

The figure below vividly illustrates this fact, as it compares the best estimate and 90% confidence range of the earth's ECS as used by the IWG (calibrated Roe and Baker) against findings in the scientific literature published since January 1, 2011.

Whereas the IWG ECS distribution has a median value of 3.0°C and 5th and 95th percentile values of 1.72°C and 7.14°C, respectively, the corresponding values averaged from the recent scientific literature are ~2.0°C (median), ~1.1°C (5th percentile), and ~3.5°C (95th percentile).

These differences will have large and significant impacts on the SCC determination.



CAPTION: The median (indicated by the small vertical line) and 90% confidence range (indicated by the horizontal line with arrowheads) of the climate sensitivity estimate used by the Interagency Working Group on the Social Cost of Carbon Climate (Roe and Baker, 2007) is indicated by the top black arrowed line. The average of the similar values from 22 different determinations reported in the recent scientific literature is given by the grey arrowed line (second line from the top). The sensitivity estimates from the 32 individual determinations of the ECS as reported in new research published after January 1, 2011 are indicated by the colored arrowed lines. The arrows indicate the 5 to 95% confidence bounds for each estimate along with the best estimate (median of each probability density function; or the mean of multiple estimates; colored vertical line). Ring et al. (2012) present four estimates of the climate sensitivity and the red box encompasses those estimates. Likewise, Bates (2016) presents eight estimates and the green box encompasses them. Spencer and Braswell (2013) produce a single ECS value best-matched to ocean heat content observations and internal radiative forcing.

In addition to recent studies aimed at directly determining the equilibrium climate sensitivity (included in the chart above), there have been several other major studies which have produced results which qualitatively suggest a climate sensitivity lower than mainstream (e.g. Roe and Baker calibration) estimates. Such studies include new insights on cloud condensation nuclei and cosmic rays (Kirkby et al., 2016), radiative forcing of clouds (Bellouin, 2016; Stevens, 2015), cloud processes (Mauritsen and Stevens, 2015) and the underestimation of terrestrial CO₂ uptake (Sun et al., 2014).

The IWG2010 report noted that, concerning the low end of the ECS distribution, its determination reflected a greater degree of certainty that a low ECS value could be excluded than did the IPCC. From the IWG2010 (p. 14):

“Finally, we note the IPCC judgment that the equilibrium climate sensitivity “is very likely larger than 1.5°C.” Although the calibrated Roe & Baker distribution, for which the probability of equilibrium climate sensitivity being greater than 1.5°C is almost 99 percent, is not inconsistent with the IPCC definition of “very likely” as “greater than 90 percent probability,” it reflects a greater degree of certainty about very low values of ECS than was expressed by the IPCC.”

In other words, the IWG used its *judgment* that the lower bound of the ECS distribution was higher than the IPCC 2007 assessment indicated. However, the collection of the recent literature on the ECS shows the IWG’s judgment to be in error. As can be seen in the chart above, the large majority of the findings on ECS in the recent literature indicate that the lower bound (i.e., 5th percentile) of the ECS distribution is lower than the IPCC 2007 assessment. And, the average value of the 5th percentile in the recent literature (~1.1°C) is 0.62°C *less* than that used by the IWG—a sizeable and important difference which will influence the SCC determination.

In fact, the abundance of literature supporting a lower climate sensitivity was at least partially reflected in the new IPCC assessment report issued in 2013. In that report, the IPCC reported:

Equilibrium climate sensitivity is *likely* in the range 1.5°C to 4.5°C (*high confidence*), *extremely unlikely* less than 1°C (*high confidence*), and *very unlikely* greater than 6°C (*medium confidence*). The lower temperature limit of the assessed *likely* range is thus less than the 2°C in the AR4...

Clearly, the IWG’s assessment of the low end of the probability density function that best describes the current level of scientific understanding of the climate sensitivity is incorrect and indefensible.

But even more influential in the SCC determination is the upper bound (i.e., 95th percentile) of the ECS probability distribution.

The IWG2010 notes (p.14) that the calibrated Roe and Baker distribution better reflects the IPCC judgment that “values substantially higher than 4.5°C still cannot be excluded.” The IWG2010 further notes that

“Although the IPCC made no quantitative judgment, the 95th percentile of the calibrated Roe & Baker distribution (7.1 °C) is much closer to the mean and the median (7.2 °C) of the 95th percentiles of 21 previous studies summarized by Newbold and Daigneault (2009). It is also closer to the mean (7.5 °C) and median (7.9 °C) of the nine truncated distributions examined by the IPCC (Hegerl, et al., 2006) than are the 95th percentiles of the three other calibrated distributions (5.2-6.0 °C).”

In other words, the IWG2010 turned towards surveys of the scientific literature to determine its assessment of an appropriate value for the 95th percentile of the ECS distribution. Now, some seven years later, the scientific literature tells different story.

Instead of a 95th percentile value of 7.14°C, as used by the IWG2010, a survey of the recent scientific literature suggests a value of ~3.5°C—more than 50% lower.

And this is very significant and important difference because the high end of the ECS distribution has a large impact on the SCC determination—a fact frequently commented on by the IWG2010.

For example, from IWG2010 (p.26):

“As previously discussed, low probability, high impact events are incorporated into the SCC values through explicit consideration of their effects in two of the three models as well as the use of a probability density function for equilibrium climate sensitivity. Treating climate sensitivity probabilistically results in more high temperature outcomes, which in turn lead to higher projections of damages. Although FUND does not include catastrophic damages (in contrast to the other two models), its probabilistic treatment of the equilibrium climate sensitivity parameter will directly affect the non-catastrophic damages that are a function of the rate of temperature change.”

And further (p.30):

Uncertainty in extrapolation of damages to high temperatures: The damage functions in these IAMs are typically calibrated by estimating damages at moderate temperature increases (e.g., DICE [Dynamic Integrated Climate and Economy] was calibrated at 2.5 °C) and extrapolated to far higher temperatures by assuming that damages increase as some power of the temperature change. Hence, estimated damages are far more uncertain under more extreme climate change scenarios.

And the entirety of Section V “A Further Discussion of Catastrophic Impacts and Damage Functions” of the IWG 2010 report describes “tipping points” and “damage functions” that are probabilities assigned to different values of global temperature change. Table 6 from the IWG2010 indicated the probabilities of various tipping points.

Table 6: Probabilities of Various Tipping Points from Expert Elicitation -

Possible Tipping Points	Duration before effect is fully realized (in years)	Additional Warming by 2100		
		0.5-1.5 C	1.5-3.0 C	3-5 C
Reorganization of Atlantic Meridional Overturning Circulation	about 100	0-18%	6-39%	18-67%
Greenland Ice Sheet collapse	at least 300	8-39%	33-73%	67-96%
West Antarctic Ice Sheet collapse	at least 300	5-41%	10-63%	33-88%
Dieback of Amazon rainforest	about 50	2-46%	14-84%	41-94%
Strengthening of El Niño-Southern Oscillation	about 100	1-13%	6-32%	19-49%
Dieback of boreal forests	about 50	13-43%	20-81%	34-91%
Shift in Indian Summer Monsoon	about 1	Not formally assessed		
Release of methane from melting permafrost	Less than 100	Not formally assessed.		

The likelihood of occurrence of these low probability, high impact, events (“tipping points”) is *greatly* diminished under the new ECS findings. The average 95th percentile value of the new literature survey is only ~3.5°C indicating a very low probability of a warming reaching 3-5°C by 2100 as indicated in the 3rd column of the above Table and thus a significantly lower probability that such tipping points will be reached. This new information will have a large impact on the final SCC determination using the IWG’s methodology.

The size of this impact has been directly investigated.

In their *Comment on the Landmark Legal Foundation Petition for Reconsideration of Final Rule Standards for Standby Mode and Off Mode Microwave Ovens*, Dayaratna and Kreutzer (2013) ran the DICE model using the distribution of the ECS as described by Otto et al. (2013)—a paper published in the recent scientific literature which includes 17 authors, 15 of which were lead authors of chapters in the recent Intergovernmental Panel on Climate Change’s *Fifth Assessment Report*. The most likely value of the ECS reported by Otto et al. (2013) was described as “2.0°C, with a 5–95% confidence interval of 1.2–3.9°C.” Using the Otto et al. (2013) ECS distribution in lieu of the distribution employed by the IWG (2013), dropped the SCC by 42 percent, 41 percent, and 35 percent (for the 2.5%, 3.0%, 5.0% discount rates, accordingly). This is a significant decline.

In subsequent research, Dayaratna and Kreutzer (2014) examined the performance of the FUND (Framework for Uncertainty, Negotiation, and Distribution) model, and found that it too, produced a greatly diminished value for the SCC when run with the Otto et al. distribution of the equilibrium climate sensitivity. Using the Otto et al. (2013) ECS distribution in lieu of the

distribution employed by the IWG (2013), dropped the SCC produced by the FUND model to \$11, \$6, \$0 compared with the original \$30, \$17, \$2 (for the 2.5%, 3.0%, 5.0% discount rates, accordingly). Again, this is a significant decline.

The Dayaratna and Kreutzer (2014) results using FUND were in line with alternative estimates of the impact of a lower climate sensitivity on the FUND model SCC determination.

Waldhoff et al. (2011) investigated the sensitivity of the FUND model to changes in the ECS. Waldhoff et al. (2011) found that changing the ECS distribution such that the mean of the distribution was lowered from 3.0°C to 2.0°C had the effect of lowering the SCC by 60 percent (from a 2010 SCC estimate of \$8/ton of CO₂ to \$3/ton in \$1995). While Waldhoff et al. (2011) examined FUNDv3.5, the response of the current version (v3.8) of the FUND model should be similar.

Additionally, the developer of the PAGE (Policy Analysis of the Greenhouse Effect) model, affirmed that the SCC from the PAGE model, too drops by 35% when the Otto et al. (2013) climate sensitivity distribution is employed (Hope, 2013).

More recently, the FUND and DICE model were run with equilibrium climate sensitivities that were determined by Lewis and Curry (2014) in an analysis which updated and expanded upon the results of Otto et al. (2013). In Dayaratna et al. (2017), the probability density function (pdf) for the equilibrium climate sensitivity determined from an energy budget model (Lewis and Curry, 2014) was used instead of the Roe and Baker calibrated pdf used by the IWG. In doing so, Dayaranta et al. (2017) report:

“In the DICE model the average SCC falls by 30-50% depending on the discount rate, while in the FUND model the average SCC falls by over 80%. The span of estimates across discount rates also shrinks considerably, implying less sensitivity to this parameter choice...Furthermore the probability of a negative SCC (implying CO₂ emissions are a positive externality) jumps dramatically using an empirical ECS distribution.”

These studies make clear that the strong dependence of the social cost of carbon on the distribution of the estimates of the equilibrium climate sensitivity (including the median, and the upper and lower certainty bounds) requires that the periodic updates to the IWG SCC determination must include a critical examination of the scientific literature on the topic of the equilibrium climate sensitivity, not merely kowtowing to the IPCC assessment. There is no indication that the IWG undertook such an independent examination. But what is clear, is that the IWG did *not* alter its probability distribution of the ECS between its 2010, 2013, 2015, and 2016 SCC determinations, despite a large and growing body of scientific literature that substantially alters and better defines the scientific understanding of the earth’s ECS. It is unacceptable that a supposed “updated” social cost of carbon does not include updates to the science underlying a critical and key aspect of the SCC.

I note that there has been one prominent scientific study in the recent literature which has argued, on the basis of recent observations of lower tropospheric mixing in the tropics, for a rather high

climate sensitivity (Sherwood et al., 2014). This research, however, suffers from too narrow a focus. While noting that climate models which best match the apparent observed behavior of the vertical mixing characteristics of the tropical troposphere tend to be the models with high climate sensitivity estimates, the authors fail to make note that these same models are the ones whose projections make the *worst* match to observations of the evolution of global temperature during the past several decades.

While Sherwood et al. (2014) prefer models that better match their observations in one variable, the same models actually do *worse* in the big picture than do models which lack the apparent accuracy in the processes that Sherwood et al. (2014) describe. The result can only mean that there must still be even bigger problems with *other* model processes which must more than counteract the effects of the processes described by Sherwood et al.

This illustrates the inherent problems with “tuning” climate models to try to best reproduce a known set of observations—efforts to force climate models to better emulate one set of physical behaviors can degrade their performance on other ones. Voosen (2016) recently reported on the climate modelling community efforts to be more open and transparent with their multitude of (secret) “tuning” procedures. Voosen’s reporting was eye-opening not only in revealing the degree to which climate models are tuned and the significant role that tuning plays in model projections, but as to the reasons why modelers have not wanted to be up front about their methods. I reproduce an extended and relevant excerpt here:

At their core, climate models are about energy balance. They divide Earth up into boxes, and then, applying fundamental laws of physics, follow the sun’s energy as it drives phenomena like winds and ocean currents. Their resolution has grown over the years, allowing current models to render Earth in boxes down to 25 kilometers a side. They take weeks of supercomputer time for a full run, simulating how the climate evolves over centuries.

When the models can’t physically resolve certain processes, the parameters take over—though they are still informed by observations. For example, modelers tune for cloud formation based on temperature, atmospheric stability, humidity, and the presence of mountains. Parameters are also used to describe the spread of heat into the deep ocean, the reflectivity of Arctic sea ice, and the way that aerosols, small particles in the atmosphere, reflect or trap sunlight.

It’s impossible to get parameters right on the first try. And so scientists adjust these equations to make sure certain constraints are met, like the total energy entering and leaving the planet, the path of the jet stream, or the formation of low marine clouds off the California coast. Modelers try to restrict their tuning to as few knobs as possible, but it’s never as few as they’d like. It’s an art and a science. “It’s like reshaping an instrument to compensate for bad sound,” Stevens says.

Indeed, whether climate scientists like to admit it or not, nearly every model has been calibrated precisely to the 20th century climate records—otherwise it would

have ended up in the trash. “It’s fair to say all models have tuned it,” says Isaac Held, a scientist at the Geophysical Fluid Dynamics Laboratory, another prominent modeling center, in Princeton, New Jersey.

For years, climate scientists had been mum in public about their “secret sauce”: What happened in the models stayed in the models. The taboo reflected fears that climate contrarians would use the practice of tuning to seed doubt about models—and, by extension, the reality of human-driven warming. “The community became defensive,” [Bjorn] Stevens [of the Max Planck Institut] says. “It was afraid of talking about things that they thought could be unfairly used against them.” Proprietary concerns also get in the way. For example, the United Kingdom’s Met Office sells weather forecasts driven by its climate model. Disclosing too much about its code could encourage copycats and jeopardize its business.

But modelers have come to realize that disclosure could reveal that some tunings are more deft or realistic than others. It’s also vital for scientists who use the models in specific ways. They want to know whether the model output they value—say, its predictions of Arctic sea ice decline—arises organically or is a consequence of tuning. [Gavin] Schmidt [Head of NASA’s Goddard Institute for Space Studies, which, ironically concentrates on earth’s climate] points out that these models guide regulations like the U.S. Clean Power Plan, and inform U.N. temperature projections and calculations of the social cost of carbon. “This isn’t a technical detail that doesn’t have consequence,” he says. “It has consequence.”

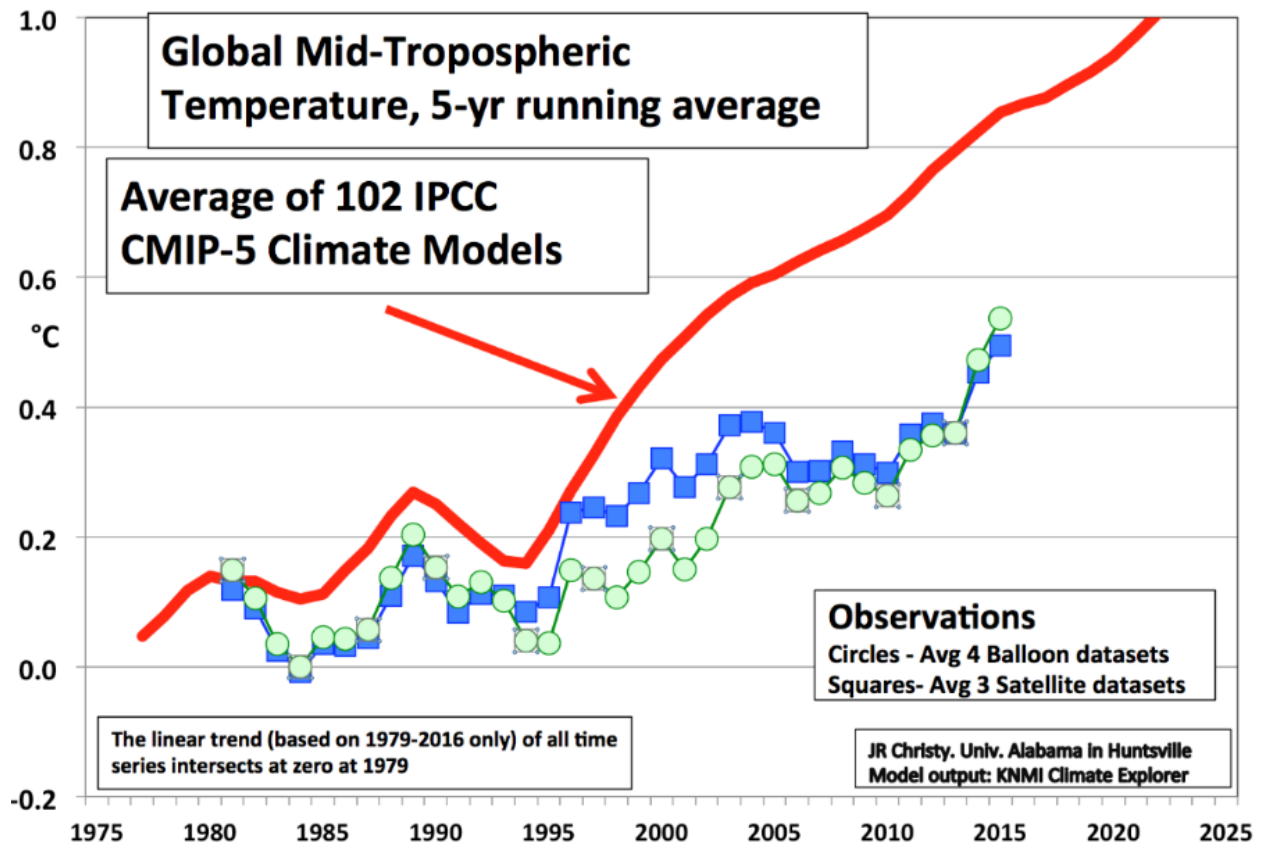
Recently, while preparing for the new model comparisons, MPIM modelers got another chance to demonstrate their commitment to transparency. They knew that the latest version of their model had bugs that meant too much energy was leaking into space. After a year spent plugging holes and fixing it, the modelers ran a test and discovered something disturbing: The model was now overheating. Its climate sensitivity—the amount the world will warm under an immediate doubling of carbon dioxide concentrations from preindustrial levels—had shot up from 3.5°C in the old version to 7°C, an implausibly high jump.

MPIM hadn’t tuned for sensitivity before—it was a point of pride—but they had to get that number down. Thorsten Mauritsen, who helps lead their tuning work, says he tried tinkering with the parameter that controlled how fast fresh air mixes into clouds. Increasing it began to ratchet the sensitivity back down. “The model we produced with 7° was a damn good model,” Mauritsen says. But it was not the team’s best representation of the climate as they knew it.

That climate modelers were worried about being open about their methodologies for fear that “contrarians” would “unfairly” use such procedures against them indicates that the modeling community is more interested in climate policy (that may find support in their model projections) than climate science (which would welcome criticism aimed at producing a better understanding of the physical processes driving the earth’s climate). Given the degree of “secret sauce” mixed

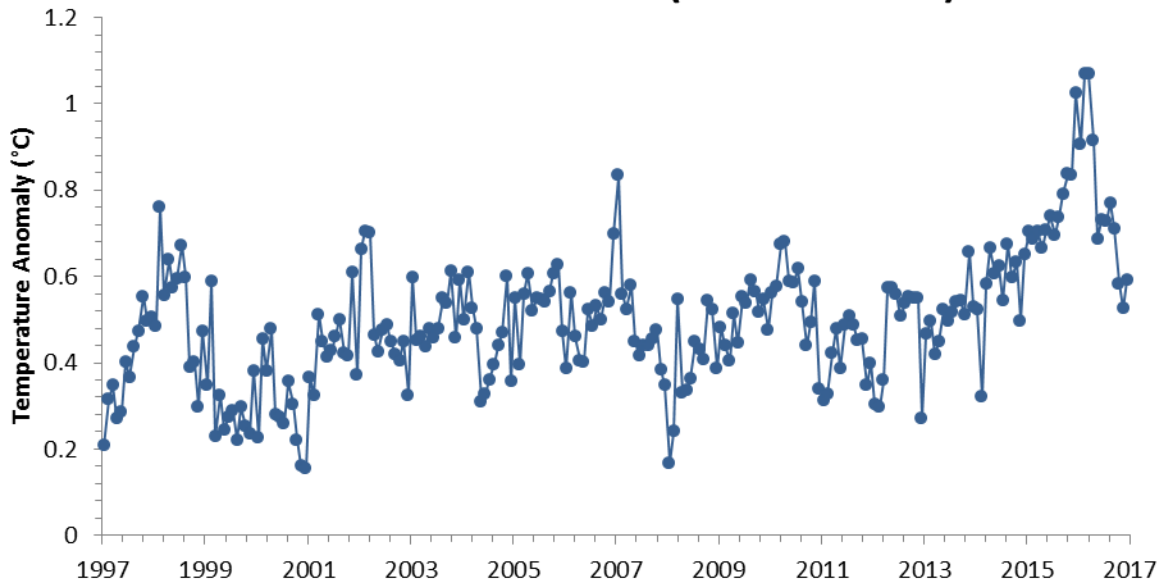
into the models at this point in time, a healthy dose of skepticism regarding the verisimilitude of climate model output is warranted.

But even with all the model tuning that takes place, the overall model collective is *still* warming the world much faster than it actually is. As shown by Christy (2016, and updates), there is a gross departure of “reality” from model predictions. Christy (2016) noted that “for the global bulk troposphere [roughly the bottom 40,000 feet of the atmosphere], the models overwarm the atmosphere by a factor of about 2.5.” The warming influence of a large and naturally occurring El Niño event has, temporarily, added a blip to the end of the observational record. But despite this short-term natural warming event, collectively the models still produce about twice as much warming as can be found in the real world over the past 38 years. And as the warming of the recent strong El Niño event fades (global surface temperatures have returned most of the way to pre-El Niño levels; see Figures below), the model/real world discrepancy will start to grow once again.

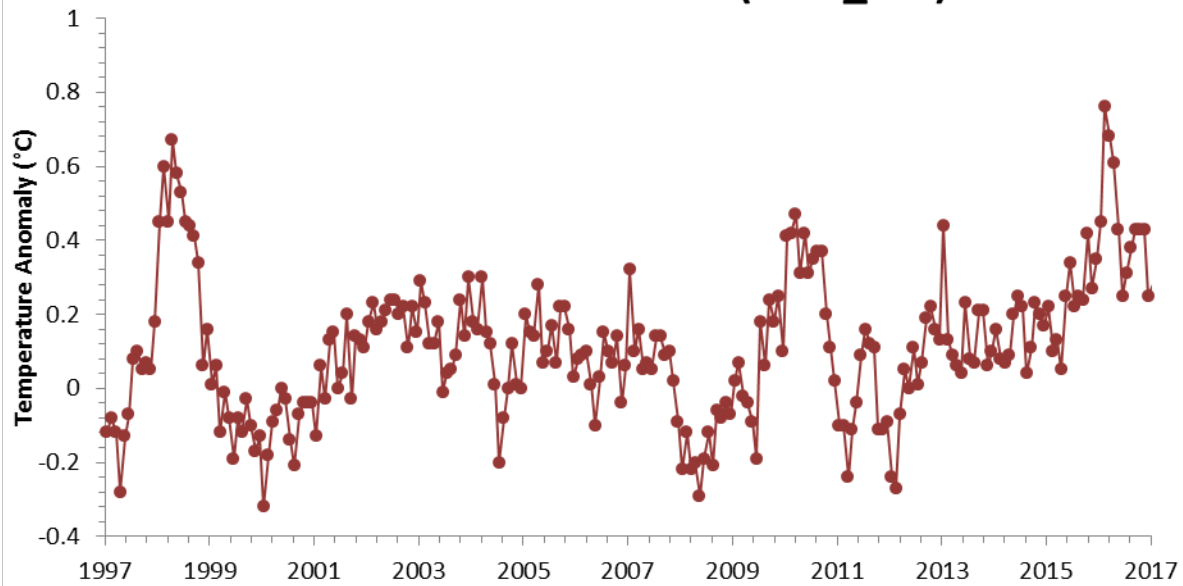


CAPTION: Five-year running mean temperatures predicted by the UN’s climate models, and observed lower atmospheric temperatures from weather balloons and satellites (figure courtesy of John Christy). The last point is a four-year running mean, and the first two are three and four, respectively.

Surface Observations (HadCRUT4v5)



Satellite Observations (UAH_MT)

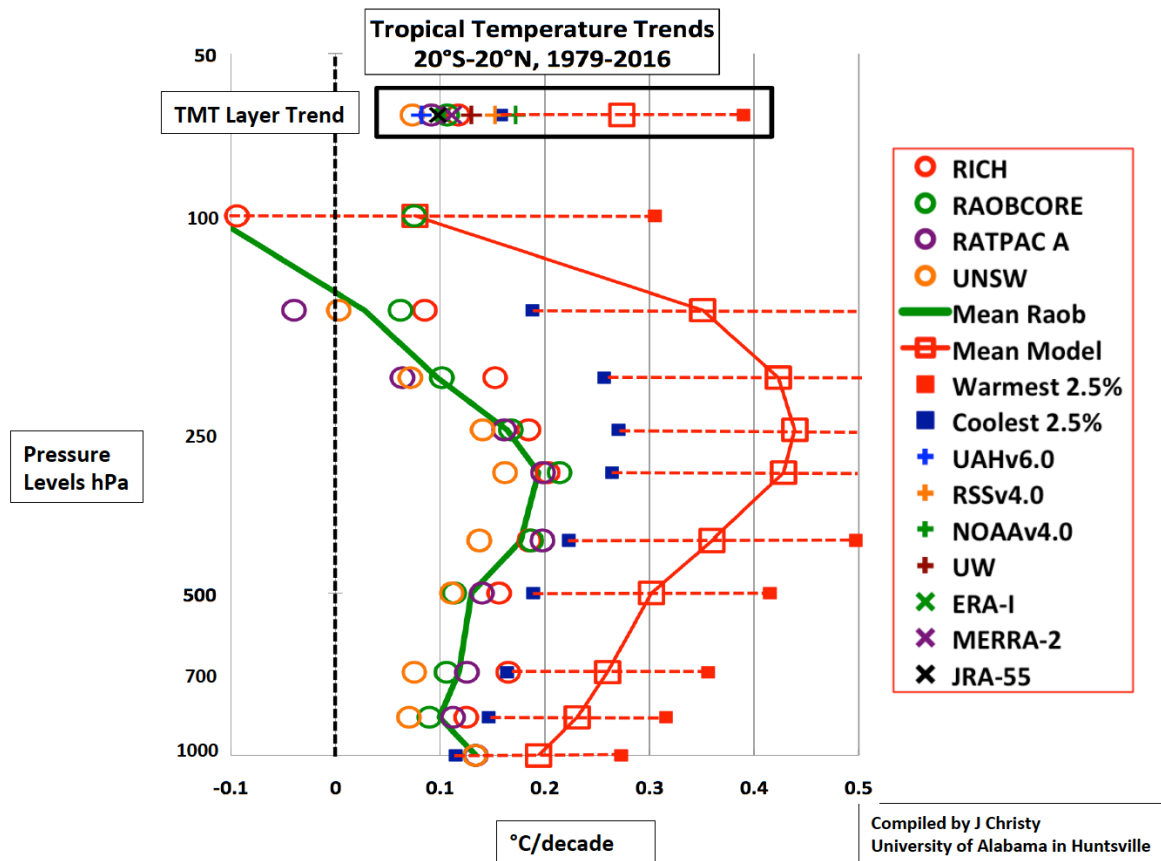


CAPTION: Monthly temperature anomalies, January 1997 through December 2016 (surface observations; top) and January 1997 through January 2017 (satellite observations of the mid-troposphere; bottom) show the impact of the strong 2016 El Niño event and the fading warmth since. The surface readings are from the Climate Research Unit at the University of East Anglia, and the satellite readings are from University of Alabama-Huntsville.

Another way to assess model performance is to compare model projection with observed trends in the vertical dimension of the atmosphere. Here again, as shown in the Figure below, models grossly produce much more warming than has been observed. This chart, courtesy of the University of Alabama at Huntsville's Dr. John Christy, focuses on the tropics (between 20S and 20N)—the area where climate models project the greatest amount of warming through the atmosphere. The communal failure of the models is abject.

The characteristics of the vertical profile of temperature are important environmental variables in that it is the vertical temperature distribution that determines atmospheric stability. When the lapse rate—the difference between the lowest layers and higher levels—is large, the atmosphere is unstable. Instability is the principal source for global precipitation. Although models can be (and are) tuned to mimic changes in surface temperatures, the same can't be done as easily for the vertical profile of temperature changes. As the figure indicates, the air in the middle troposphere is warming far more slowly than has been predicted, even more slowly than the torpid surface warming. Consequently, the difference between the surface and the middle troposphere has become slightly greater, a condition which should produce a very slight increase in average precipitation. On the other hand, the models forecast that the difference between the surface and the middle troposphere should become less, a condition which would add pressure to decrease global precipitation.

The models are therefore making systematic errors in their precipitation projections. That has a dramatic effect on the resultant climate change projections. When the surface is wet, which is what occurs after rain, the sun's energy is directed toward the evaporation of that moisture rather than to directly heating the surface. In other words, much of what is called "sensible weather" (the kind of weather a person can sense) is determined by the vertical distribution of temperature. If the popular climate models get that wrong (which is what is happening), then all the subsidiary weather may also be incorrectly specified.



CAPTION: Tropical (20°S to 20°N) temperature trends(1979-2016) throughout the vertical atmosphere as projected by climate models (red squares, with uncertainty) and as observed by radiosondes carried aloft by weather balloons (colored circles represent different data compilations). The red line is the model mean and the green line is the observed mean. The trend in the bulk lower atmosphere (middle troposphere) from several different satellite data compilations (colored plus signs, top box) and several reanalysis datasets (colored crosses, top box) is compared with the model projection for the same layer in the box at the top of the figure. (Figure courtesy of John Christy)

These results argue strongly against the reliability of the Sherwood et al. (2014) conclusion and instead provide robust observational evidence that the climate sensitivity has been overestimated by both climate models, and the IWG alike.

Agricultural Impacts of Carbon Fertilization

Carbon dioxide is known to have a large positive impact on vegetation (e.g., Zhu et al., 2016), with literally thousands of studies in the scientific literature demonstrating that plants (including crops) grow stronger, healthier, and more productive under conditions of increased carbon dioxide concentration. A study (Idso, 2013) reviewed a large collection of such literature as it applies to the world’s 45 most important food crops (making up 95% of the world’s annual agricultural production).

Idso (2013) summarized his findings on the increase in biomass of each crop that results from a 300ppm increase in the concentration of carbon dioxide under which the plants were grown. This table is reproduced below, and shows that the typical growth increase exceeds 30% in most crops, including 8 of the world's top 10 food crops (the increase was 24% and 14% in the other two).

Idso (2013) found that the increase in the atmospheric concentration of carbon dioxide that took place during the period 1961-2011 was responsible for increasing global agricultural output by 3.2 trillion dollars (in 2004-2006 constant dollars). Projecting the increases forward based on projections of the increase in atmospheric carbon dioxide concentration, Idso (2013) expects carbon dioxide fertilization to increase the value of agricultural output by 9.8 trillion dollars (in 2004-2006 constant dollars) during the 2012-2050 period.

Average percentage increase in biomass of each of the world's 45 most important food crops under an increase of 300ppm of carbon dioxide.

Crop	% Biomass Change	Crop	% Biomass Change
Sugar cane	34.0%	Rye	38.0%
Wheat	34.9%	Plantains	44.8%
Maize	24.1%	Yams	47.0%
Rice, paddy	36.1%	Groundnuts, with shell	47.0%
Potatoes	31.3%	Rapeseed	46.9%
Sugar beet	65.7%	Cucumbers and gherkins	44.8%
Cassava	13.8%	Mangoes, mangosteens, guavas	36.0%
Barley	35.4%	Sunflower seed	36.5%
Vegetables fresh nes	41.1%	Eggplants (aubergines)	41.0%
Sweet potatoes	33.7%	Beans, dry	61.7%
Soybeans	45.5%	Fruit Fresh Nes	72.3%
Tomatoes	35.9%	Carrots and turnips	77.8%
Grapes	68.2%	Other melons (inc.cantaloupes)	4.7%
Sorghum	19.9%	Chillies and peppers, green	41.1%
Bananas	44.8%	Tangerines, mandarins, clem.	29.5%
Watermelons	41.5%	Lettuce and chicory	18.5%
Oranges	54.9%	Pumpkins, squash and gourds	41.5%
Cabbages and other brassicas	39.3%	Pears	44.8%
Apples	44.8%	Olives	35.2%
Coconuts	44.8%	Pineapples	5.0%
Oats	34.8%	Fruit, tropical fresh nes	72.3%
Onions, dry	20.0%	Peas, dry	29.2%
Millet	44.3%		

This is a large positive externality, and one that is insufficiently modeled in the IAMs relied upon by the IWG in determining the SCC.

In fact, only one of the three IAMs used by the IWG has any substantial impact from carbon dioxide fertilization, and the one that does, underestimates the effect by approximately 2-3 times.

The FUND model has a component which calculates the impact on agricultural as a result of carbon dioxide emissions, which includes not only the impact on temperature and other climate changes, but also the direct impact of carbon dioxide fertilization. The other two IAMs, DICE and PAGE by and large do not (or only do so extremely minimally; DICE includes the effect to a larger degree than PAGE). Consequently, lacking this large and positive externality, the SCC calculated by the DICE and PAGE models is significantly larger than the SCC determined by the FUND model (for example, see Table A5, in the IWG 2013 report).

But even the positive externality that results from carbon dioxide fertilization as included in the FUND model is too small when compared with the Idso (2013) estimates. FUND (v3.7) uses the following formula to determine the degree of crop production increase resulting from atmospheric carbon dioxide increases (taken from Anthoff and Tol, 2013a):

CO₂ fertilisation has a positive, but saturating effect on agriculture, specified by

$$(A.4) \quad A_{t,r}^f = \gamma_r \ln \frac{CO_{2t}}{275}$$

where

- A^f denotes damage in agricultural production as a fraction due to the CO₂ fertilisation by time and region;
- t denotes time;
- r denotes region;
- CO_2 denotes the atmospheric concentration of carbon dioxide (in parts per million by volume);
- 275 ppm is the pre-industrial concentration;
- γ is a parameter (see Table A, column 8-9).

Column 8 in the table below shows the CO₂ fertilization parameter (γ_r) used in FUND for various regions of the world (Anthoff and Tol, 2013b). The average CO₂ fertilization effect across the 16 regions of the world is 11.2%. While this number is neither areally weighted, nor weighted by the specific crops grown, it is clear that 11.2% is much lower than the average fertilization effect compiled by Idso (2013) for the world's top 10 food crops (35%). Further, Idso's fertilization impact is in response to a 300ppm CO₂ increase, while the fertilization parameter in the FUND model is multiplied by $\ln(CO_{2t}/275)$ which works out to 0.74 for a 300ppm CO₂ increase. This multiplier further reduces the 16 region average to 8.4% for the CO₂ fertilization effect—some 4 times smaller than the magnitude of the fertilization impact identified by Idso (2013).

Although approximately four times too small, the impact of the fertilization effect on the SCC calculation in the FUND model is large.

According to Waldhoff et al. (2011), if the CO₂ fertilization effect is turned off in the FUND model (v3.5) the SCC increases by 75% from \$8/tonCO₂ to \$14/tonCO₂ (in 1995 dollars). In another study, Ackerman and Munitz (2012) find the effective increase in the FUND model to be even larger, with CO₂ fertilization producing a positive externality of nearly \$15/tonCO₂ (in 2007 dollars).

Impact of climate change on agriculture in FUND model.

	Rate of change (% Ag. Prod/ 0.04°C)		δ_r^l		δ_r^q		CO ₂ fertilisation (% Ag. Prod)	
USA	-0.021	(0.176)	0.026	(0.021)	-0.012	(0.018)	8.90	(14.84)
CAN	-0.029	(0.073)	0.092	(0.080)	-0.016	(0.009)	4.02	(6.50)
WEU	-0.039	(0.138)	0.022	(0.002)	-0.014	(0.013)	15.41	(11.83)
JPK	-0.033	(0.432)	0.046	(0.022)	-0.024	(0.030)	23.19	(36.60)
ANZ	-0.015	(0.142)	0.040	(0.071)	-0.016	(0.037)	10.48	(8.50)
EEU	-0.027	(0.062)	0.048	(0.097)	-0.018	(0.048)	9.52	(5.14)
FSU	-0.018	(0.066)	0.042	(0.075)	-0.016	(0.039)	6.71	(5.48)
MDE	-0.022	(0.032)	0.042	(0.071)	-0.017	(0.037)	9.43	(2.66)
CAM	-0.034	(0.061)	0.064	(0.043)	-0.030	(0.043)	16.41	(5.38)
SAM	-0.009	(0.060)	0.003	(0.005)	-0.004	(0.003)	5.96	(5.04)
SAS	-0.014	(0.021)	0.025	(0.024)	-0.011	(0.018)	5.80	(1.64)
SEA	-0.009	(0.482)	0.014	(0.004)	-0.010	(0.008)	8.45	(41.81)
CHI	-0.013	(0.075)	0.043	(0.076)	-0.017	(0.040)	19.21	(6.13)
NAF	-0.016	(0.023)	0.033	(0.043)	-0.014	(0.027)	7.27	(1.90)
SSA	-0.011	(0.026)	0.024	(0.034)	-0.010	(0.020)	5.05	(2.20)
SIS	-0.050	(0.103)	0.043	(0.077)	-0.017	(0.040)	23.77	(8.64)

Standard deviations are given in brackets.

Clearly, had the Idso (2013) estimate of the CO₂ fertilization impact been used instead of the one used in FUND the resulting positive externality would have been much larger, and the resulting net SCC been much lower.

This is just for one of the three IAMs used by the IWG. Had the more comprehensive CO₂ fertilization impacts identified by Idso (2013) been incorporated in all the IAMs, the three-model average SCC used by the IWG would be been greatly lowered, and likely even become negative in some IAM/discount rate combinations.

In its 2015 “Response to Comments Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866,” the IWG admits to the disparate ways that CO₂ fertilization is included in the three IAMs. Nevertheless, the IWG quickly dismisses this as a problem in that they claim the IAMs were selected “to reflect a reasonable range of modeling choices and approaches that collectively reflect the current literature on the estimation of damages from CO₂ emissions.”

This logic is blatantly flawed. Two of the IAMs do not reflect the “current literature” on a key aspect relating to the direct impact of CO₂ emissions on agricultural output, and the third only partially so.

CO₂ fertilization is a known physical effect from increased carbon dioxide concentrations. By including the results of IAMs that do not include known processes that have a significant impact on the end product must disqualify them from contributing to the final result. The inclusion of results that are known *a priori* to be wrong can only contribute to producing a less accurate

answer. Results should only be included when they attempt to represent known processes, not when they leave those processes out entirely.

The justification from the IWG (2015) that “[h]owever, with high confidence the IPCC (2013) stated in its Fifth Assessment Report (AR5) that ‘[b]ased on many studies covering a wide range of regions and crops, negative impacts of climate change on crop yields have been more common than positive ones’” is completely irrelevant as CO₂ fertilization is an impact that is apart from “climate change.” And further, the IAMs do (explicitly in the case of FUND and DICE or implicitly in the case of PAGE) include damage functions related to the climate change impacts on agriculture. So not only is the IWG justification irrelevant, it is inaccurate as well. The impact of CO₂ fertilization on agricultural output and its impact on lowering the SCC *must* be considered.

Additional Climate Model Parameter Misspecifications

In addition to the outdated climate sensitivity distribution and the insufficient handling of the carbon dioxide fertilization effect, there has also been identified a misspecification of some of the critical parameters within the underlying box models that drive the pace and shape of the future climate evolution in the IAMs.

A recent analysis (Lewis, 2016) finds that the physically-based two-box climate model inherent in the DICE IAM is fit with physically unrealistic ocean characteristics. According to Lewis (2016):

In the DICE 2-box model, the ocean surface layer that is taken to be continuously in equilibrium with the atmosphere is 550 m deep, compared to estimates in the range 50–150 m based on observations and on fitting 2-box models to AOGCM responses. The DICE 2-box model’s deep ocean layer is less than 200 m deep, a fraction of the value in any CMIP5 AOGCM, and is much more weakly coupled to the surface layer. Unsurprisingly, such parameter choices produce a temperature response time profile that differs substantially from those in AOGCMs and in 2-box models with typical parameter values. As a result, DICE significantly overestimates temperatures from the mid-21st century on, and hence overestimates the SCC and optimum carbon tax, compared with 2-box models having the same ECS and TCR but parameter values that produce an AOGCM-like temperature evolution.

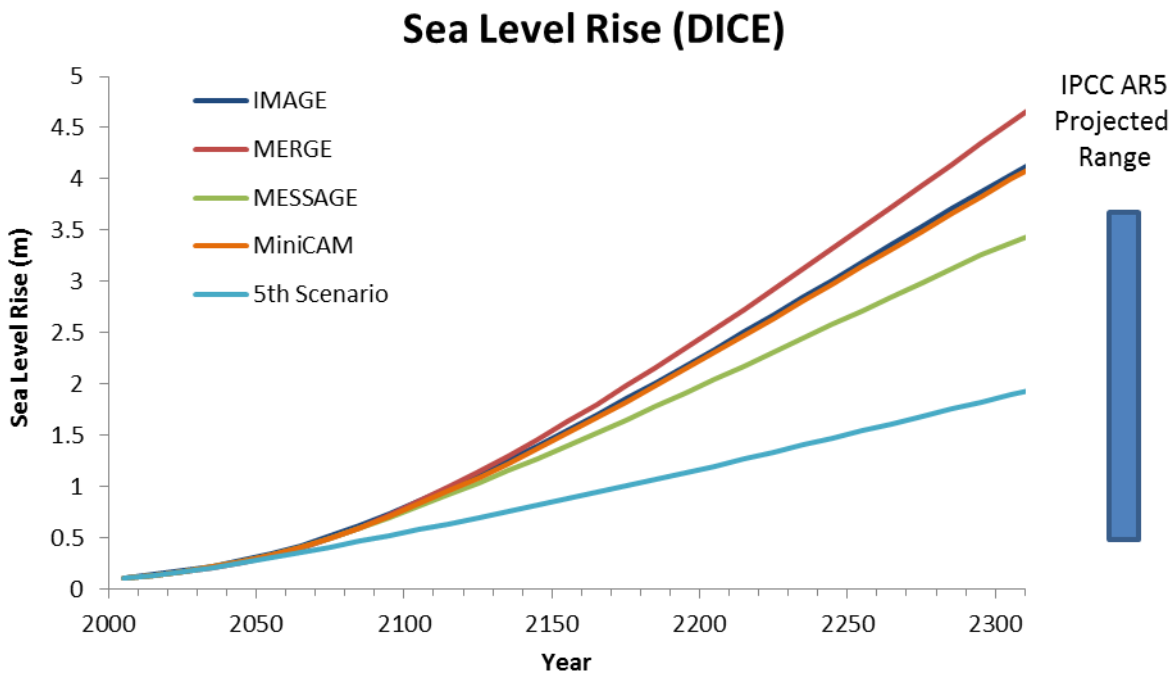
When the DICE 2-box model is parametrized with values for the ocean layers that are in line with established estimates, the value of the social cost of carbon that results is reduced by one-quarter to one-third during the 21st century. Lewis further point out that notes that “The climate response profile in FUND and in PAGE, the other two IAMs used by the US government to assess the SCC, appear to be similarly inappropriate, suggesting that they also overestimate the SCC.”

Ultimately, Lewis (2016) concludes:

It seems rather surprising that all three of the main IAMs have climate response functions with inappropriate, physically unrealistic, time profiles. In any event, it is worrying that governments and their scientific and economic advisers have used these IAMs and, despite considering what [equilibrium climate sensitivity] and/or [transient climate sensitivity] values or probability distributions thereof to use, have apparently not checked whether the time profiles of the resulting climate responses were reasonable.

Sea Level Rise

The sea level rise module in the DICE model used by the IWG2013/2015/2016 produces future sea level rise values that far exceed mainstream projections and are unsupported by the best available science. The sea level rise projections from more than half of the scenarios (IMAGE, MERGE, MiniCAM) exceed even the highest end of the projected sea level rise by the year 2300 as reported in the *Fifth Assessment Report* (AR5) of the Intergovernmental Panel on Climate Change (see figure).



CAPTION: Projections of sea level rise from the DICE model (the arithmetic average of the 10,000 Monte Carlo runs from each scenario) for the five scenarios examined by the IWG2013 compared with the range of sea level rise projections for the year 2300 given in the IPCC AR5 (see AR5 Table 13.8). (DICE data provided by Kevin Dayaratna and David Kreutzer of the Heritage Foundation).

How the sea level rise module in DICE was constructed is inaccurately characterized by the IWG (and misleads the reader). The IWG report describes the development of the DICE sea level rise scenario as:

“The parameters of the four components of the SLR module are calibrated to match consensus results from the IPCC’s Fourth Assessment Report (AR4).⁶”

However, in IWG footnote “6” the methodology is described this way (Nordhaus, 2010):

“The methodology of the modeling is to use the estimates in the IPCC Fourth Assessment Report (AR4).”

“Using estimates” and “calibrating” are two completely different things. Calibration implies that the sea level rise estimates produced by the DICE sea level module behave similarly to the IPCC sea level rise projections and instills a sense of confidence in the casual reader that the DICE projections are in accordance with IPCC projections. However this is not the case. Consequently, the reader is misled.

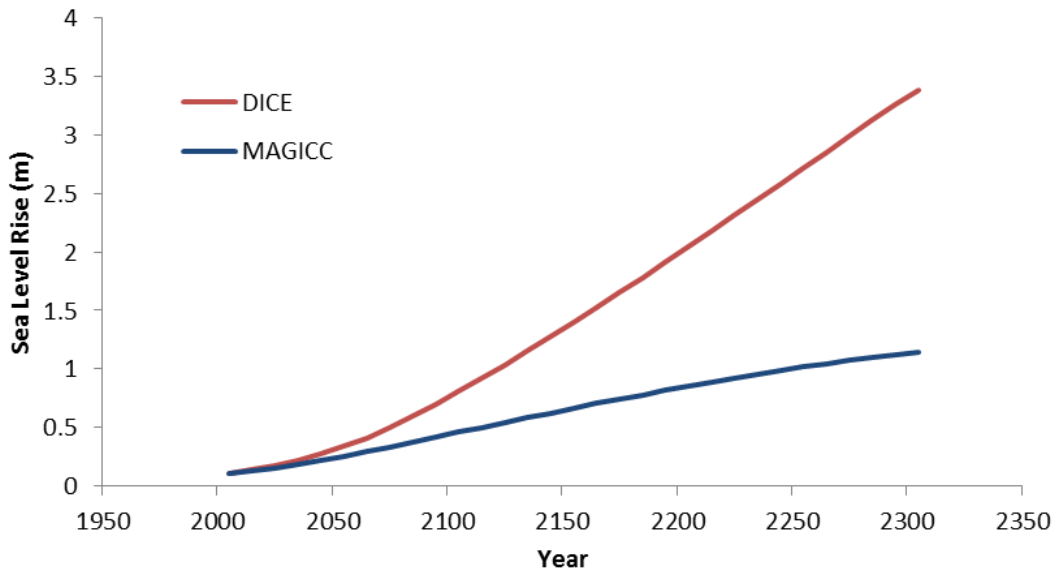
In fact, the DICE estimates are much higher than the IPCC estimates. This is even recognized by the DICE developers. From the same reference as above:

“The RICE [DICE] model projection is in the middle of the pack of alternative specifications of the different Rahmstorf specifications. Table 1 shows the RICE, base Rahmstorf, and average Rahmstorf. *Note that in all cases, these are significantly above the IPCC projections in AR4.*” [emphasis added]

That the DICE sea level rise projections are far above mainstream estimated can be further evidenced by comparing them with the results produced by the IWG-accepted MAGICC modelling tool (in part developed by the EPA and available from <http://www.cgd.ucar.edu/cas/wigley/magicc/>).

Using the MESSAGE scenario as an example, the sea level rise estimate produced by MAGICC for the year 2300 is 1.28 meters—a value that is less than 40% of the average value of 3.32 meters produced by the DICE model when running the same scenario (see figure below).

Projected Sea Level Rise (MESSAGE)



CAPTION: Projected sea level rise resulting from the MESSAGE scenario produced by DICE (red) and MAGICC (blue).

The justification given for the high sea level rise projections in the DICE model (Nordhaus, 2010) is that they well-match the results of a “semi-empirical” methodology employed by Rahmstorf (2007) and Vermeer and Rahmstorf (2009).

However, subsequent science has proven the “semi-empirical” approach to projecting future sea level rise unreliable. For example, Gregory et al. (2012) examined the assumption used in the “semi-empirical” methods and found them to be unsubstantiated. Gregory et al (2012) specifically refer to the results of Rahmstorf (2007) and Vermeer and Rahmstorf (2009):

The implication of our closure of the [global mean sea level rise, GMSLR] budget is that a relationship between global climate change and the rate of GMSLR is weak or absent in the past. The lack of a strong relationship is consistent with the evidence from the tide-gauge datasets, whose authors find acceleration of GMSLR during the 20th century to be either insignificant or small. It also calls into question the basis of the semi-empirical methods for projecting GMSLR, which depend on calibrating a relationship between global climate change or radiative forcing and the rate of GMSLR from observational data (Rahmstorf, 2007; Vermeer and Rahmstorf, 2009; Jevrejeva et al., 2010).

In light of these findings, the justification for the very high sea level rise projections (generally exceeding those of the IPCC AR5 and far greater than the IWG-accepted MAGICC results) produced by the DICE model is called into question and can no longer be substantiated.

Given the strong relationship between sea level rise and future damage built into the DICE model, there can be no doubt that the SCC estimates from the DICE model are higher than the

best science would allow and consequently, should not be accepted by the IWG as a reliable estimate of the social cost of carbon.

And here again, the IWG (2015) admits that these sea level rise estimates are an outlier on the high end, yet retains them in their analysis by claiming that they were interested in representing a “range” of possible outcomes. But, even the IWG (2015) admits that the IPCC AR5 assigned “a low confidence in projections based on such [semi-empirical] methods.” It is internally inconsistent to claim the IPCC as an authority for limiting the range of possibilities explored by the IAMs (which it did in the case of equilibrium climate sensitivity) and then go outside the IPCC to justify including a wildly high estimate of sea level rise. Such inconsistencies characterize the IWG response to comments and weaken confidence in them.

I did not investigate the sea level rise projections from the FUND or the PAGE model, but suggest that such an analysis must be carried out prior to extending any confidence in the values of the SCC resulting from those models—confidence that, as demonstrated, cannot be assigned to the DICE SCC determinations.

Conclusion

The social cost of carbon as determined by the Interagency Working Group in their August 2016 Technical Support Document (updated from IGW reports from February 2010, November 2013, and July 2015) is unsupported by the robust scientific literature, fraught with uncertainty, illogical, and thus completely unsuitable and inappropriate for federal rulemaking. Had the IWG included a better-reasoned and more inclusive review of the current scientific literature, the social cost of carbon estimates would have been considerably reduced with a value likely approaching zero. Such a low social cost of carbon would obviate the arguments behind the push for federal greenhouse gas regulations.

References

Ackerman, F., and C. Munitz, 2012. Climate damages in the FUND model: a disaggregated analysis. *Ecological Economics*, **77**, 219-224.

Aldrin, M., et al., 2012. Bayesian estimation of climate sensitivity based on a simple climate model fitted to observations of hemispheric temperature and global ocean heat content. *Environmetrics*, doi: 10.1002/env.2140.

Annan, J.D., and J.C Hargreaves, 2011. On the generation and interpretation of probabilistic estimates of climate sensitivity. *Climatic Change*, **104**, 324-436.

Anthoff, D., and R.S.J. Tol, 2013a. The climate framework for uncertainty, negotiation and distribution (FUND), technical description, version 3.7, <http://www.fund-model.org/publications>

Anthoff, D., and R.S.J. Tol, 2013b. The climate framework for uncertainty, negotiation and distribution (FUND), tables, version 3.7, <http://www.fund-model.org/publications>

Bates, J. R., 2016. Estimating Climate Sensitivity Using Two-zone Energy Balance Models. *Earth and Space Science*, doi: 10.1002/2015EA000154

Bellouin, N., 2016. The interaction between aerosols and clouds. Weather and Climate @Reading, <http://blogs.reading.ac.uk/weather-and-climate-at-reading/2016/1053/>.

Christy, J.R., 2016. Testimony before the House Committee on Science, Space, and Technology, February 2, 2016.

Dayaratna, K., and D. Kreutzer, 2013. Comment on the Energy Efficiency and Renewable Energy Office (EERE) Proposed Rule: 2013-08-16 Energy Conservation Program for Consumer Products: Landmark Legal Foundation; Petition for Reconsideration; Petition for Reconsideration; Request for Comments, <http://www.regulations.gov/#!documentDetail;D=EERE-2013-BT-PET-0043-0024>

Dayaratna, K., and D. Kreutzer, 2014. Unfounded FUND: Yet another EPA model not ready for the Big Game, <http://www.heritage.org/research/reports/2014/04/unfounded-fund-yet-another-epa-model-not-ready-for-the-big-game>.

Dayaratna, K., R. McKittrick, and D. Kreutzer, 2017. Empirically-constrained climate sensitivity and the social cost of carbon. Accepted, *Climate Change Economics*.

Gregory, J., et al., 2012. Twentieth-century global-mean sea-level rise: is the whole greater than the sum of the parts? *Journal of Climate*, doi:10.1175/JCLI-D-12-00319.1, in press.

Hargreaves, J.C., et al., 2012. Can the Last Glacial Maximum constrain climate sensitivity? *Geophysical Research Letters*, **39**, L24702, doi: 10.1029/2012GL053872

Hope, C., 2013. How do the new estimates of transient climate response affect the social cost of CO₂? <http://www.chrishopepolicy.com/2013/05/how-do-the-new-estimates-of-transient-climate-response-affect-the-social-cost-of-co2/> (last visited May 5, 2014)

Idso, C. 2013. *The positive externalities of carbon dioxide: Estimating the monetary benefits of rising CO₂ concentrations on global food production*. Center for the Study of Carbon Dioxide and Global Change, 30pp.

Intergovernmental Panel on Climate Change, 2007. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon, S., et al. (eds). Cambridge University Press, Cambridge, 996pp.

Intergovernmental Panel on Climate Change, 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Final Draft Accepted in the 12th Session of

Working Group I and the 36th Session of the IPCC on 26 September 2013 in Stockholm, Sweden.

Kirkby, J., et al., 2016. Ion-induced nucleation of pure biogenic particles. *Nature*, **533**, 521–526, [doi:10.1038/nature17953](https://doi.org/10.1038/nature17953).

Lewis, N. 2013. An objective Bayesian, improved approach for applying optimal fingerprint techniques to estimate climate sensitivity. *Journal of Climate*, doi: 10.1175/JCLI-D-12-00473.1.

Lewis, N. and J.A. Curry, C., 2014. The implications for climate sensitivity of AR5 forcing and heat uptake estimates. *Climate Dynamic*, 10.1007/s00382-014-2342-y.

Lewis, N., 2016. Abnormal climate response of the DICE IAM – a trillion dollar error? *Climate Etc.*, last accessed, August 16, 2016, <https://judithcurry.com/2016/08/15/abnormal-climate-response-of-the-dice-iam-a-trillion-dollar-error/>

Lindzen, R.S., and Y-S. Choi, 2011. On the observational determination of climate sensitivity and its implications. *Asia-Pacific Journal of Atmospheric Science*, **47**, 377-390.

Loehle, C., 2014. A minimal model for estimating climate sensitivity. *Ecological Modelling*, **276**, 80-84.

Masters, T., 2013. Observational estimates of climate sensitivity from changes in the rate of ocean heat uptake and comparison to CMIP5 models. *Climate Dynamics*, doi:10.1007/s00382-013-1770-4

Mauritsen, T. and B. Stevens, 2015. Missing iris effect as a possible cause of muted hydrological change and high climate sensitivity in models. *Nature Geoscience*, **8**, 346-351, doi:10.1038/ngeo2414.

Nordhaus, W., 2010. Projections of Sea Level Rise (SLR), http://www.econ.yale.edu/~nordhaus/homepage/documents/SLR_021910.pdf

Otto, A., F. E. L. Otto, O. Boucher, J. Church, G. Hegerl, P. M. Forster, N. P. Gillett, J. Gregory, G. C. Johnson, R. Knutti, N. Lewis, U. Lohmann, J. Marotzke, G. Myhre, D. Shindell, B. Stevens, and M. R. Allen, 2013. Energy budget constraints on climate response. *Nature Geoscience*, **6**, 415-416.

Rahmstorf, S., 2007. A semi-empirical approach to projecting future sea-level rise. *Science*, **315**, 368–370, doi:10.1126/science.1135456.

Ring, M.J., et al., 2012. Causes of the global warming observed since the 19th century. *Atmospheric and Climate Sciences*, **2**, 401-415, doi: 10.4236/acs.2012.24035.

Schmittner, A., et al. 2011. Climate sensitivity estimated from temperature reconstructions of the Last Glacial Maximum. *Science*, **334**, 1385-1388, doi: 10.1126/science.1203513.

Sherwood, S. C., S. Bony, and J-D. Dufresne, 2014. Spread in model climate sensitivity traced to atmospheric convective mixing. *Nature*, **505**,37-42, doi:10.1038/nature12829.

Skeie, R. B., T. Berntsen, M. Aldrin, M. Holden, and G. Myhre, 2014. A lower and more constrained estimate of climate sensitivity using updated observations and detailed radiative forcing time series. *Earth System Dynamics*, **5**, 139–175.

Spencer, R. W., and W. D. Braswell, 2013. The role of ENSO in global ocean temperature changes during 1955-2011 simulated with a 1D climate model. *Asia-Pacific Journal of Atmospheric Science*, doi:10.1007/s13143-014-0011-z.

Stevens, B., 2015. Rethinking the lower bound on aerosol radiative forcing. *Journal of Climate*, **28**, 4794-4819, doi: 10.1175/JCLI-D-14-00656.1.

Sun, Y., et al., 2014. Impact of mesophyll diffusion on estimated global land CO₂ fertilization. *Proceedings of the National Academy of Science*, **111**, 15774-15779, doi: 10.1073/pnas.1418075111.

van den Bergh, J.C.J.M., and W.J.W. Botzen, 2014. A lower bound to the social cost of CO₂ emissions. *Nature Climate Change*, **4**, 253-258, doi:10.1038/NCLIMATE2135.

Vermeer, M. and S. Rahmstorf, 2009. Global sea level linked to global temperature. *Proceedings of the National Academy of Sciences*, **106**, 51, 21527–21532, doi:10.1073/pnas.0907765106.

Voosen, P., 2016. Climate scientists open up their black boxes to scrutiny. *Science*, **354**, 401-402.

Waldhoff, S., Anthoff, D., Rose, S., and R.S.J. Tol, 2011. The marginal damage costs of different greenhouse gases: An application of FUND. *Economics, The Open-Access E-Journal*, No. 2011-43, <http://www.economics-ejournal.org/economics/discussionpapers/2011-43>

Wigley, T.M.L., et al. MAGICC/SCENGEN v5.3. Model for the Assessment of Greenhouse-gas Induced Climate Change/A Regional Climate Scenario Generator. <http://www.cgd.ucar.edu/cas/wigley/magicc/>

Zhu, Z., et al., 2016. Greening of the Earth and its drivers. *Nature Climate Change*, doi: 10.1038/nclimate3004