C O M M E N T

LEARNING TO SEE THROUGH THE BLACK BOX: DEVELOP X-RAY VISION THROUGH ALGORITHMIC INTUITION

by Mohit Chhabra

Mohit Chhabra is Technical Lead and Advisor, Natural Resources Defense Council.

Environmental, natural resource, and energy planning will continue to rely on increasingly complex algorithms. Are these processes then also doomed to be inaccessible to key stakeholders? Hopefully not.

There are multiple steps to ensuring process and participatory equity. There is ease of access to the process, access to necessary information, and then there is the matter of having the right information to be able to meaningfully impact outcomes of algorithm-assisted decisionmaking processes.

In *How Algorithm-Assisted Decisionmaking Is Influencing Environmental Law and Climate Adaptation*, Prof. Sonya Ziaja proposes a useful framework for increasing participation and integrating process equity in algorithm-assisted decisionmaking. Guiding questions around uncertainty, transparency, and stakeholder collaboration provide a starting point to investigate and create accountability for climate models.

The next step to facilitating meaningful participation in analytically complex processes requires stakeholders to develop algorithmic intuition. Model developers and process facilitators have the ability and the necessary information to bring stakeholders along. Stakeholders and decisionmakers can do their part by asking the right questions.

In this Comment, I propose an additional set of questions for prospective participants, both technical and non-technical, to build familiarity, or intuition, of a given algorithm. *Algorithmic intuition* requires understanding the scope of the analysis, key parameters, and causal relationships between parameters and outcomes of the model at hand. Model developers and process facilitators can do their part by proactively providing this information to stakeholders.

With this knowledge, attorneys, advocates, and policy analysts should be better positioned to determine whether intervening in an algorithm-assisted decisionmaking process is worth their time. And if they decide to participate, they can focus their limited resources on the most influential aspects of the model. Decisionmakers can apply the principles of algorithmic intuition to translate seemingly precise model results to binding policy decisions.

I. Algorithms Are Inherent to Most Parts of Climate Policy

Algorithms are inherent to climate change policy-related debate, development, and regulatory decisionmaking. For instance, reports such as those by the Intergovernmental Panel on Climate Change (IPCC), that apply climate models to forecast tomorrow's devastation due to today's and yesterday's greenhouse gas (GHG) emissions, are responsible for the increasing prevalence of climate change in policy debate.[1] Moreover, the very question at the heart of most, if not all, climate policy debate is analytic and economic: whether and to what extent avoiding (algorithmically estimated) future climate damages justifies near-term spending to curb emissions.

Further, even though legislative debate to set climate change policy is often normative value-driven, policy implementation usually requires reliance on algorithms. Consider the case of California's electricity sector. The California Legislature, through Senate Bill 100, set a goal of getting to a zero-carbon electric sector by 2045.[2] Although there isn't much evidence that legislators considered climate models or economic analysis to determine the exact amount of, and timeline for, future carbon reduction, the California Energy Commission must apply an electric-sector capacity expansion model to determine how much, and what type of, new clean energy resources are required

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1. Timothy Cama, *"Answer to the Code Red": Dems Cite IPCC for Climate Agenda*, E&E Daily (Aug. 10, 2021, 6:50 AM), https://www.eenews.net/articles/answer-to-the-code-red-dems-cite-ipcc-for-climate-agenda/.
2. S. B. 100, 2017-2018 Leg. Sess. (Cal. 2018) (enacted), https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201720180SB100.

to comply with Senate Bill 100 while keeping electricity reliable and affordable.[3]

The Social Cost of Greenhouse Gas (SC-GHG) is another such example. The SC-GHG is the present value of future damages due to an additional ton of anthropogenic GHG emissions. The basic concept of the SC-GHG is straightforward: regulatory agencies should account for environmental externalities when evaluating the benefits and costs of any proposed regulation. A higher SC-GHG value means that regulators, like the U.S. Environmental Protection Agency (EPA), will find higher monetary benefits from reducing carbon emissions. Higher monetary benefits justify stricter and costlier GHG emission reduction standards. Stakeholder incentives are apparent: organizations with a vested interest in carbon-emitting technologies mostly argue for a lower SC-GHG value and vice versa.

Estimating the value of the SC-GHG is anything but straightforward. It requires a combination of legal, climate, and economic analyses. This calculation applies multiple complex models, which in turn are informed by long lists of inputs and assumptions. The SC-GHG is opaque to most stakeholders. Its theoretical and algorithmic complexity inhibits useful participation by stakeholders and is susceptible to both inadvertent and malicious distortions.

II. A Black Box: The Social Cost of Greenhouse Gases

The SC-GHG is calculated via four modules: a global economic and GHG projection module; a climate module; an economic module; and a discounting module. With much simplification, the process can be summarized as follows. Economists and experts develop multiple baseline scenarios of future global economic growth and associated GHG emissions that span hundreds of years. Modelers apply global climate models to these baseline scenarios to determine the future climate impacts of an incremental ton of GHG emissions. The economic damage from these climate impacts, such as loss in productivity and increased mortality due to extreme heat, is then inferred. These future economic damages are then discounted to the present using the full Ramsey function, which adjusts the discount rate for each future year based on forecasted economic conditions. The outcome is a stream of dollar values that regulators apply in benefit cost analysis.

The Interagency Working Group (IWG) under President Barack Obama recommended a mean SC-GHG of around $51 per ton of GHG emissions; the Donald Trump Administration changed some key inputs and assumptions and recommended an SC-GHG of under $7[4]; and EPA recently updated the methodology, inputs, and assumptions to recommend a mean value of $190.[5] Public comments to EPA were predictable and guided by political leanings and economic priorities.[6]

Following the framework proposed by Professor Ziaja starts to demystify this process. To EPA's credit, they provide detailed documentation on how they calculate the SC-GHG. The documentation contains links to all relevant studies and models that inform the SC-GHG. The documentation also explains how it accounted for uncertainty in various steps.[7] EPA's updates are based on extensive publicly accessible recommendations by the National Academy of Sciences.[8] EPA also released its report on the SC-GHG update three months before soliciting public comment.

This is a vast amount of information. Although the logic of each component of the analysis is explicable, and a list of inputs that informed the final output are available, this information doesn't help advocates or subject matter experts assess the extent to which they can influence or contribute to the final estimate.

III. Algorithmic Intuition Gives X-Ray Vision

Algorithmic intuition is built by understanding an algorithm-assisted decisionmaking process' scope, key parameters, and causal relationships.

- Scope: what is the scope of the model? Would expanding or contracting the model scope significantly influence the outcome?

3. *See* Liz G. et al., Cal. Energy Comm'n, 2021 SB 100 Joint Agency Report, Achieving 100 Percent Clean Electricity in California: An Initial Assessment (Sept. 2021), https://www.energy.ca.gov/publications/2021/2021-sb-100-joint-agency-report-achieving-100-percent-clean-electricity.
4. *See* U. S. Gov't Accountability Off., Social Cost of Carbon: Identifying a Federal Entity to Address the National Academies' Recommendations Could Strengthen Regulatory Analysis 1 (June 2002), https://www.gao.gov/assets/gao-20-254.pdf.
5. *See* Supplementary Material for the Regulatory Impact Analysis for the Supplemental Proposed Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review" EPA External Review Draft of Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, EPA 3 (September 2022) [hereinafter EPA's SC-GHG Report]. Note that each of these SC-GHG estimates are approximate in that they reflect different discount rates and should be expressed in terms of the same nominal dollars for an accurate comparison. These estimates suffice for an order of magnitude comparison.
6. The Heritage Foundation, commenting on a related ruling that an older and lower SC-GHG estimate states that the SC-GHG process is easily influenced by political leanings and that the Obama-era IWG values are vast over-estimates. *See* Marlo Lewis, Competitive Enterprise Institute (CEI), and Kevin D. Dayaratna, Heritage Foundation, Comment on EPA, Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Gas Sector Climate Review; Supplemental Notice of Proposed Rulemaking, 87 FR 74702, Dec. 6, 2022, https://www.regulations.gov/comment/EPA-HQ-OAR-2021-0317-2413; *see also* https://www.regulations.gov/comment/EPA-HQ-OAR-2021-0317-2237. On the other hand, groups like Our Children's Trust argued that the EPA's SC-GHG estimate should be even higher. Environmental organizations also supported EPA's update and argue that some appropriate changes would cause the SC-GHG to increase further. See, for example: https://www.regulations.gov/comment/EPA-HQ-OAR-2021-0317-2253 and https://www.nrdc.org/sites/default/files/nrdc_comments_epa_sc-ghg_update-20230213.pdf.
7. See, for example, EPA's SC-GHG Report at 23 and 25.
8. Nat'l Acad. of Sci., Eng'g, & Med., Valuing Climate Damages, Estimating the Social Cost of Carbon Dioxide (2017), https://nap.nationalacademies.org/read/24651/chapter/1.

Figure 1. Sensitivities of the SC-GHG to Key Parameters by Rennert et al.

Table 1 | Evolution of mean SC-CO_2 from DICE-2016R to this study

Row	Scenario	Mean SC-CO_2 ($ per tCO2)	Incremental change ($ per tCO2)	Share of total change (%)
a	DICE-2016R	44		
b	GIVE with DICE damage function, 3% near-term discount rate	59	15	11
c	GIVE with sectoral damages, 3% near-term discount rate	80	21	15
d	This study: GIVE with sectoral damages, 2% near-term discount rate	185	105	74

All SC-CO_2 values are expressed in 2020 US dollars per metric tonne of CO_2. Row a represents the SC-CO_2 using base DICE-2016R deterministic. The mean SC-CO_2 of $44 per tCO_2 is similar to the value previously estimated from IWG DICE-2010 of $46 per tCO_2 at a 3% discount rate, after converting to 2020 dollars[65]. Row b then retains the DICE-2016R damage function but otherwise deploys GIVE under discounting parameters of $\rho=0.8\%$, $\eta=1.57$, which are consistent with a 3% near-term discount rate (see Methods section 'Discounting' for descriptions of ρ and η). Row c replaces the DICE-2016R damage function with our sectoral damage functions, and row d then uses our preferred discounting parameters from this study of $\rho=0.2\%$, $\eta=1.24$, which are consistent with a 2% near-term discount rate. The final row represents the preferred mean value from this study.

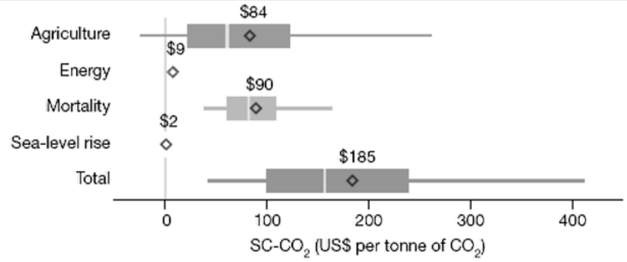

Fig. 3 | Partial SC-CO_2 estimates and uncertainty levels strongly differ across the four climate damage sectors. Box and whisker plots for the climate damage sectors included in the GIVE model, based on partial SC-CO_2 estimates for each sector. The figure depicts the median (centre white line), 25%–75% quantile range (box width), and 5%–95% quantile range (coloured horizontal lines) partial SC-CO_2 values. Black diamonds highlight each sector's mean partial SC-CO_2, with the numeric value written directly above. All SC-CO_2 values are expressed in 2020 US dollars per metric tonne of CO_2.

- Key parameters: which inputs and assumptions have an outsized impact on a model's outputs?
- Causal relationships: what is the direction and the order of magnitude of change in output due to a change in key parameters?

Once a stakeholder has intuition for an algorithmic tool, they can determine the extent to which they can influence the outcome of the model. By better understanding what most drives the outcome, they can better focus their advocacy and resources. Decisionmakers can apply this algorithmic intuition to better interpret model outputs with the nuance and skepticism necessary to make binding policy decisions.

Model developers should provide this information to stakeholders, and stakeholders should demand this information when participating in algorithm-assisted decisionmaking processes. Requesting a clear explanation of analysis scope seems straightforward, however drawing the boundaries between what a model can and can't consider has real implications on the outcomes. Key questions for the SC-GHG include how far in time it should estimate damages to, and whether an agency of the United States should limit its accounting of climate damages to whatever occurs within the country's geographic boundaries. There are policy and legal arguments for both questions. The Trump Administration limited the scope of the SC-GHG analysis to only those damages from GHG emissions that occur domestically. This limitation is a big reason why the Trump Administration's SC-GHG estimate was so low. This key part of the analysis, establishing an appropriate scope, is something non-technical stakeholders can influence.

Identifying key parameters and their causal relationships to the output requires both transparency and analysis. Model developers should provide stakeholders with a list of parameters that the model is most sensitive to. Stakeholders should request a sensitivity analysis on each of these key parameters to understand how and to what extent these parameters influence the output. One way to conduct the sensitivity analysis is to first hold all parameters but one constant, then vary the parameter of interest by an order of magnitude, then rerun the model. Repeating this for all key parameters would tell a clear story of how different key parameters impact the outcome of the model.

Fortunately, recent research published in *Nature* conducts such an analysis on the SC-GHG.[9] The study, an update to the SC-GHG using up-to-date scientific and economic data, also analyzes the sensitivity of the SC-GHG estimate to key model parameters. Their findings, reproduced below, illustrate that future climate damages to agricultural output and mortality impact the SC-GHG more than impacts on other sectors. The other noteworthy fact is that these are the only four sectors investigated, which further speaks to better understanding and refining the scope of the analysis.[10] Finally, as the left side of the figure illustrates, the discount rate matters much more than most modeling details. Reducing the discount rate from 3% to 2% increases the study's estimate of the SC-GHG from $80 per ton to $185.

9. Kevin Rennert et al., *Comprehensive Evidence Implies A Higher Social Cost of CO_2*, 610 Nature J. 687, 687-92 (2022), https://doi.org/10.1038/s41586-022-05224-9.
10. See, for example, EPA's SC-GHG Report at 73.

IV. An Example of How to Use X-Ray Vision to Effectively Participate in Black Box Processes

Using this framework for algorithmic intuition, interested participants now know what kind of expertise to leverage and what sub-components of the analysis warrant their limited resources. Attorneys and non-technical staff at environmental organizations can apply this framework of algorithmic intuition to influence the outcome of a seemingly black box process. Consider the example of the SC-GHG.

Should the SC-GHG scope be limited to one country's geographic boundary given the spillover effects of climate change, the interconnectedness of the global economy, and the fact that GHGs are a global pollutant whose impact is independent of where they were emitted? Non-technical participants can provide evidence and normative value-based arguments to answer this key question. Attorneys can provide the legal basis for whether and how the global impact of domestic pollutants needs to be accounted for. Environmental organizations can also comment on the fact that the SC-GHG analyses do not account for the irreversible harm that climate change will inflict on ecosystems and biodiversity therein. Without the inclusion of these impacts, SC-GHG estimates are bound to be conservative. Finally, advocates can reach out to economists to better understand the arguments for including lower discount rates and then request an analysis that more accurately values future damages from present-day GHG emissions.