Addressing Criticisms Towards Integrated Assessment Models: What scholars are missing using the Global Change Analysis Model as a case study.

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

As we rapidly approach the 2° threshold of climate warming, organizations around the world are turning to more advanced modeling techniques to coordinate a path forward. Having models that accurately predict the social, economic, and physical impacts of these pathways is critical to properly address the climate issue and minimize unforeseen consequences. As such, decision makers around the world are increasingly relying on integrated assessment models (IAMs) such as the Global Change Analysis Model (GCAM), which is an IAM developed in the United States by the Pacific Northwest National Laboratory, to assess pathways for achieving global goals of climate change mitigation (Evans & Hausfather, 2018). With this reliance, it is imperative that we understand the strengths and weaknesses of models so that they may be continuously improved. This forms the basis of my research: I investigate what is currently missing or misunderstood by scholars when it comes to IAMs using GCAM as a case study.

The integrated assessment model family as a whole faces a high level of scrutiny from scholars because of their increased use; as such critiques of IAMs are quite common in the current academic landscape. However, the critics of IAMs, including critics of GCAM, tend to focus primarily on model results and ignore, or do not adequately consider, their inputs. By failing to address data used by IAMs, we are missing out on a crucial component of understanding them. There are two potential harmful side effects to this lack of knowledge: 1) the models continue to be critiqued to the point where they are no longer used, and we lose a powerful tool to address our climate problem, or 2) we rely heavily on models to inform decisions without having enough information, potentially leading to very costly mistakes.

The field of STS research lacks adequate analysis of data methods used in IAMs for climate change mitigation. I argue that the critics of integrated assessment models are missing a component of their evaluation because they do not consider data and their context within the models. Using GCAM's data system as a case study, I show that understanding the data helps address existing criticisms. I address three commonly cited complaints with integrated assessment models by analyzing scenario assumptions and raw data present in GCAM's data system. To support my analysis, I draw on the concept of the relational view of data, as defined by Sabina Leonelli (2015, 2019). This framework centers on the idea that data are not objective and must be understood within their context, which is how they have been created and/or managed by the people that use them to interpret a certain reality.

Background

Integrated assessment models in the context of climate change refer to a family of tools that combine various strands of knowledge to explore how societal choices and behaviors affect the physical world. The United Nation's Intergovernmental Panel on Climate Change (IPCC) uses a suite of IAMs to assess potential pathways of climate change mitigation. One of these models is the Global Change Analysis Model (GCAM), which is used for analysis in this paper. GCAM was chosen for this analysis because it is completely open source and is developed here in the United States. Additionally, the entire data system for GCAM is available for download in R and is very well-documented (Bond-Lamberty et al., 2022).

Figure 1 provides a simplified overview of how data are processed to serve as inputs to the GCAM model. In the GCAM data system, (raw) data are pulled from several sources, such as the US department of Agriculture (USDA), Food and Agriculture Organization (FAO), International Energy Agency (IEA), Shared Socioeconomic Pathways (SSPs), and others. Though based in the United States, the model is a collection of international efforts and as such pulls resources and data from a wide variety of sources, both national and international. The

GCAM data system in R gathers data from all sources and compiles approximately 200 xml files that serve as inputs to the model.

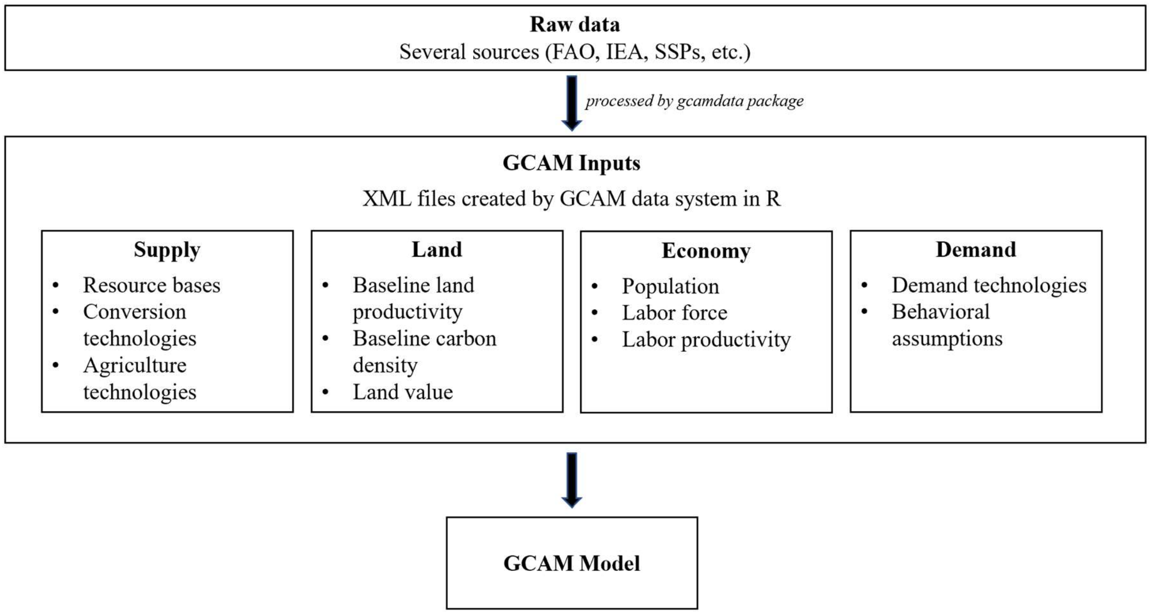

Figure 1. Schematic overview of GCAM data process

Literature Review

Increased use of IAMs by the IPCC has led to a growing level of criticism centered on the models. In the current academic landscape, critiques of the integrated assessment model family are quite common. However, while there are plenty of scholars highlighting criticisms with IAMs, they fail to adequately consider model inputs, namely data methods and assumptions. Gambhir et al. (2019) provides a comprehensive review of the IAMs featured most prominently in IPCC assessment reports, including GCAM. Of ten criticisms cited in this paper, only three relate to model inputs. These criticisms highlight scholar's issues with model assumptions: that they 1) are either inappropriate or out of date, 2) lack transparency, or 3) the model is too sensitive to them. These are all important issues that can be partially, if not fully, addressed by examining how the model's data are processed. So, while Gambhir et al. (2019) is on the right track in exploring both model inputs and outputs, there is still a big piece of the puzzle that is missing: discussion of the data.

Wilson et al. (2017) explores the suite of techniques currently being used to evaluate the performance of IAMs. The authors highlight the need for a high level of trust in IAMs if they are to serve as useful tools for analyzing long-term global climate change. However, they suggest that trust is difficult to obtain when there is not an adequate approach to evaluating these models. Six different evaluation methods are reviewed: three use (historical) observational data, two use comparison between models, and the last uses sensitivity analysis. The paper proposes the introduction of a systematic approach combining these methods of evaluation to improve the appropriateness, interpretability, credibility, and relevance of integrated assessment models. This paper serves as another example of a gap in the current discourse: there is no mention of model inputs. With inputs (data and assumptions) serving as a driver for the model results, it is important that they are incorporated into our evaluation of the reliability of IAMs.

Both papers discussed above highlight the gap in knowledge that we currently face: scholars are not paying attention to the data being used by IAMs, whether that be in evaluation techniques (Wilson et al., 2017) or direct criticisms (Gambhir et al., 2019). The data must be researched and discussed because they play a crucial role in what results are yielded. This paper demonstrates the importance of understanding a model's data by addressing three critiques presented by Gambhir et al. through a case study of the GCAM data system under the relational view.

Conceptual Framework

My analysis of the GCAM data system draws on the framework of the relational view of data, which allows me to demonstrate the necessity of context for a model to be properly understood. The framework was developed by Sabina Leonelli, and the main idea is that data can not inherently provide an answer, or some *truth* value in and of themselves. Under the relational view, data are not objective and do not speak for themselves. Rather, data are evidence that people use to interpret a certain reality, and only make sense when you consider how they were made and/or managed. Leonelli contends that it takes work to manipulate data into a usable form, and this work should be understood as a part of data's context (Leonelli, 2015, 2019). Figure 2 demonstrates how the process of scientific inquiry is defined according to the relational view. When considering this process, it is at the stage of modeling where we can understand what representational value has been assigned to data. The meticulous processing of GCAM's inputs, and its wide range of sources, speaks to this perspective on how we should understand data.

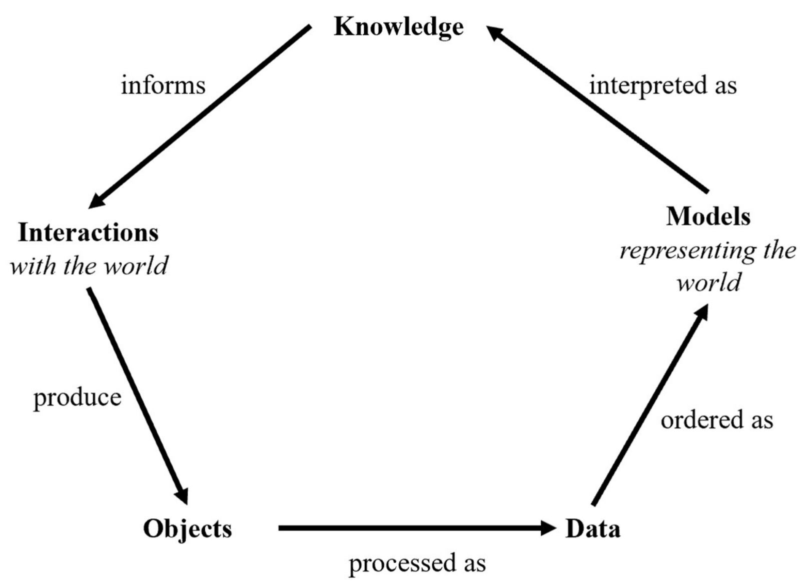

Figure 2. The process of scientific inquiry according to the relational view of data (Leonelli, 2019)

There are two ideas that stem from this main component of the relational view that are relevant to this paper. The first is that anything can be used as data. This is a side effect of the ever-growing world of data at our fingertips, but in the context of this paper, this is relevant in defining what 'data' is. Leonelli defines data as: "objects that are treated as potential or actual evidence for claims about phenomena in ways that can, at least in principle, be scrutinized and accounted for" (Leonelli, 2015). This is quite broad; therefore I offer my own definition of data that will be used throughout the remainder of this paper. I define 'data' within GCAM as not only raw data, but also the processed xml files and various assumptions programmed into the model. Second, and perhaps most importantly, Leonelli states that data are not context independent. In the same way that they cannot provide some inherent truth, data can only make sense within the context of how they are used.

Drawing on this, in the analysis that follows I show examples of how data and their context within GCAM's data system can address three common criticisms with integrated assessment models, as cited by scholars. These three criticisms are: 1) lack of transparency, 2) hypersensitivity, and 3) inappropriate assumptions. Each of these criticisms is in regard to the assumptions of GCAM, which serve as a part of its data. Under the relational view, data are 'ordered as' (Figure 2) to produce models. The context of this ordering provides understanding of the value assignment since data do not have an inherent value or truth. Looking at this process regarding the GCAM data system provides insight into the model itself, and as such addresses the criticisms mentioned above.

Analysis

It is impossible to effectively evaluate a model without an adequate understanding of it. Adequate understanding does not necessitate being able to reproduce the model in full or require an explanation of every line of code, but at the bare minimum should require knowledge of the inputs, what the model aims to solve, and its outputs. IAM critics tend to focus on the latter portion of these components, and often fail to investigate model inputs (data and assumptions). Critics are missing an important component by failing to investigate model data and their context. In the analysis that follows I address three common criticisms associated with IAMs and how understanding data through the lens of the relational view can address these criticisms, through a case study of the Global Change Analysis Model (GCAM)'s data system.

Lack of Transparency

Perhaps the most common criticism of IAMs is a lack of transparency, especially in terms of input assumptions (Gambhir et al. 2019). In response to this, I argue that understanding data within GCAM helps mitigate the lack of transparency and knowing the source, context, and process of data provides insights into the assumptions present. An example that illustrates this is the regional definitions in GCAM. Within the model, the global macroeconomy and energy system are divided into 32 geopolitical regions, including both countries and collections of countries. Outside of GDP and population, these regional definitions are relevant to all energy supply and demand related data, much of which is supplied by the International Energy Agency (IEA) (World Energy Balances - Data Product, 2022). The IEA collects data for 150 countries, and these data are then further aggregated into 32 global regions.

For individuals who are unfamiliar with GCAM, the division of regions is likely an unknown assumption. Without experience with the model, one could assume that each country is represented, or each continent, or any combination of these two. However, with some basic exploration of GCAM's data, it can be shown that the model has 32 regions. The level of aggregation can be observed within several tables in the prebuilt data file, which is accessed through the data folder in the GCAM data system in R (Joint Global Change Research Institute, 2018). Figure 3 shows one instance of how the prebuilt data in GCAM's system may be manipulated in a way that demonstrates that there are 32 regions defined in the model. The code written to obtain these results uses a grouping function to summarize emissions by region.

```
View(as_tibble(PREBUILT_DATA$L102.ceds_GFED_nonco2_tg_R_S_F) %>%
    group_by(GCAM_region_ID) %>% summarize(sum(emissions)))
```

GCAM_region_ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
sum(emissions)	10361	2804	1017	4546	7603	1730	2623	1869	948	1259	13962	1617	5205	1113	694	152

GCAM_region_ID	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
sum(emissions)	5127	2249	919	1434	2861	799	5298	787	1132	1202	814	270	4737	171	654	450

Figure 3. Instance of data manipulation to demonstrate definition of 32 regions in GCAM

The table above shows the total non-greenhouse gas emissions (units are millions of metric tons) from all sectors by GCAM region from 1970 – 2015. The values of the emissions are not what is important to note here, but the fact that there are 32 regions. As shown above, just one line of code can provide insight into what assumptions are present. Though regional resolution is a simple example, it highlights the fact that looking into the data can help resolve the lack of transparency with input assumptions. Regional definitions are just one of many assumptions within GCAM but serve as a good use case for observing how exploring model data can show what assumptions were made by programmers.

Using regional definitions as an example of an assumption within GCAM, I have shown that the critique of a lack of transparency in model assumptions can be addressed by looking at data. Some may argue that this approach is too difficult to do for individuals outside of the modeling community, because those unfamiliar with the model may not be able to track the data flows and/or understand where they come from. While I acknowledge that yes, this approach can be difficult, this difficulty is a side effect of trying to build a complex global model: in trying to model the complex world that we live in, the data and processes are going to be complex as well. Further, GCAM is not the only integrated assessment model that has been published with extensive documentation and resources. MESSAGE-GLOBIOM, another integrated assessment model used by the IPCC, is also open source and provides several resources to help new users understand the assumptions, data, and model framework (International Institute for Applied Systems Analysis, 2022). This access to documentation and code helps solve the problem, and if scholars are going to continue to critique IAMs, it is also their responsibility to fully understand them by looking at data as well as outputs.

Hypersensitivity

The second complaint with IAMs that I address is their hypersensitivity to certain model parameters. This is related to the notion of transparency because the criticism lies in the fact that we may not know what parameters the model is sensitive to. However, if we improve our knowledge of the model inputs by understanding its data, we can improve our knowledge of what the model is sensitive to. In this section, I apply the relational view to the data in two reference scenarios, or 'Shared Socioeconomic Pathways' (SSPs). These SSPs are used to define potential pathways that global society could take and were developed in a collaborative effort between teams working on the models used by the IPCC, including GCAM (Hausfather, 2018; O'Neill et al., 2014). SSP2 (middle of the road) and SSP4 (inequality) dictate how GCAM is calibrated, which means that the data changes between each scenario. The "middle of the road" scenario describes a path forward in which current trends continue, and the "inequality" scenario describes a path forward where there is a high level of inequality in and between countries, with a small elite class contributing to the majority of emissions (Calvin et al., 2017). These two scenarios were chosen for my analysis because GCAM serves as the marker model for SSP4 and is equipped with computing SSP2, which can be thought of as the control.

With these two scenarios in mind, and what their different predictions entail, we can observe differences in the data that are fed into GCAM. Table 1 provides a qualitative overview of differences between inputs in certain categories between the two scenarios. It is important to note that this table does not contain all categories and variables present between the two scenarios but is included with the goal of providing a general idea of how certain assumptions differ when GCAM is calibrated under the two scenarios. Another thing to note is that within SSP4, the medium-income group can be thought of as similar to the one group defined as in SSP2: the middle class. In other words, SSP4 highlights the inequality between the high- and low-income groups, and the medium income group can be thought of as like that of SSP2, which is the 'middle of the road'.

Table 1. Assumption comparisons between SSP2 and SSP4*

Category	**Variable**	**SSP2** middle of the road	**SSP4** Inequality *(High | Medium | Low income)*
Socioeconomics	GDP per capita in 2100	$33,307	$123,244 | $30,937 | $7,388
Technology Cost	Renewables	Med	Low | Low | Low
Fuel Preference	Renewables	Med	High | High | High
Energy Demand	Industry	Med	High | Med | Low
Agriculture & Land Use	Food Demand	Med	High | Med | Low
Pollutant Emissions	Emissions Factors	Med	High | High | High

**Adapted from information available within GCAM v6 Documentation (Bond-Lamberty et al., 2022)*

There are two important things to note from Table 1. First, in three categories (technology cost, fuel preference, and pollutant emissions), there are different assumptions for all income groups when looking at SSP4 relative to SSP2. Second, in the other categories (socioeconomics, energy demand, and food demand), assumptions of SSP2 align with that of the medium income group in SSP4. From this, we can take away the following: 1) GCAM is sensitive to the decisions of the high- and low-income groups and how their decisions are modeled, and 2) GCAM is sensitive to the data related to the categories where there are different assumptions for all income groups in SSP4 relative to SSP2. Between the two scenarios, the data that is changing are the assumptions, or how GCAM is calibrated. By looking at which assumptions change and to what extent, we can know why the model results in such different future projections: one resembling our current trajectory, and the other a world of high inequality. More in depth sensitivity analyses can be done through model runs, but the point of this example is that even qualitative understanding of data in a contextual way (under a relational view) can help grow understanding of what GCAM is sensitive to.

Inappropriate Assumptions

Finally, I conclude my analysis by responding to the criticism that the assumptions in integrated assessment models are inappropriate or simply unknowable. While this is not something that understanding the data can solve in full, if more scholars work towards a better understanding of the data the issue will improve. With more people working to understand the data within integrated assessment models, the current gap in the discourse will be closed. A quote from the British statistician George Box is relevant in this discussion: “All models are wrong, but some are useful.” To his point, there will never be a perfect model, and certainly not a perfect model of our highly complex world. However, improved knowledge of model inputs *will* allow for more adequate discussion, and lead to a more complete discourse that is not missing the discussion of data.

Conclusion

As the global economy moves forward on a path towards net-zero emissions, predictive models such as GCAM will continue to be used to understand environmental, economic, and social impacts of proposed environmental policies. It is important that we recognize both the capabilities and weaknesses of integrated modeling so that we can thoughtfully move forward on a path that is best for global society. Recognizing these strengths and weaknesses requires a more complete level of evaluation than we currently have. In this paper, I argue that the critics of IAMs are missing key pieces of evidence by not researching model input data. I support this argument by drawing on the GCAM data system to address existing criticisms with IAMs.

We can only understand the results of an integrated assessment model when we know where its data came from and what assumptions were built in. Using the relational view as a lens for my analysis, I have demonstrated how understanding data within GCAM (and therefore any IAM) can contribute to addressing three common criticisms with integrated assessment models: lack of transparency, hypersensitivity, and inappropriate assumptions. The relational view of data provides guidance on how we should understand data: that they are context dependent, and we must rely on this context to interpret it. In this paper, data are defined as the inputs to GCAM, including raw data from national and international agencies, files that have been processed to digest and compile the raw data, and assumptions set by programmers.

There are several widely used integrated assessment models, all of which have complex input processing methods and assumptions just as GCAM does. Understanding this part of the models can help address the current problems associated with them. This is not being done adequately by current scholars and as such has created a gap in research and discussion related to IAMs. As we try to chart a path forward towards a more sustainable future, it is important that we have a full picture of the models we use to predict that future and the issues that they may present.

Word Count: 3452

References

Ackerman, F., DeCanio, S. J., Howarth, R. B., & Sheeran, K. (2009). Limitations of integrated assessment models of climate change. *Climatic Change*, *95*(3), 297–315. https://doi.org/10.1007/s10584-009-9570-x

Bond-Lamberty, B., Pralit Patel, Lurz, J., Pkyle, Kvcalvin, Smith, S., Abigailsnyder, Dorheim, K. R., Russellhz, Mbins, Link, R., Skim301, Nealtg, Kanishka Narayan, Turner, S. W. D., Aaron, S., Leyang Feng, Enlochner, Cwroney, … Marideeweber. (2022). *GCAM v6 Documentation: Global Change Analysis Model (GCAM)* (gcam-v6.0). Zenodo. https://doi.org/10.5281/ZENODO.6619287

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., & Wise, M. (2017). The SSP4: A world of deepening inequality. *Global Environmental Change*, *42*, 284–296. https://doi.org/10.1016/j.gloenvcha.2016.06.010

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R. Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S. J., Snyder, A., … Wise, M. (2019). GCAM v5.1: Representing the linkages between energy, water, land, climate, and economic systems. *Geoscientific Model Development*, *12*(2), 677–698. https://doi.org/10.5194/gmd-12-677-2019

Climate Change 2022: Mitigation of Climate Change. (2022, April). https://www.ipcc.ch/report/ar6/wg3/

Evans, S., & Hausfather, Z. (2018, October 2). *Q&A: How "integrated assessment models" are used to study climate change*. Carbon Brief. https://www.carbonbrief.org/qa-how-integrated-assessment-models-are-used-to-study-climate-change/

Fuhrman, J., McJeon, H., Doney, S. C., Shobe, W., & Clarens, A. F. (2019). From zero to hero?: Why integrated assessment modeling of negative emissions technologies is hard and how we can do better. *Frontiers in Climate*, *1*. https://www.frontiersin.org/articles/10.3389/fclim.2019.00011

Gambhir, A., Butnar, I., Li, P.-H., Smith, P., & Strachan, N. (2019). A review of criticisms of integrated assessment models and proposed approaches to address these, through the lens of BECCS. *Energies*, *12*(9), Article 9. https://doi.org/10.3390/en12091747

Joint Global Change Research Institute. (2018). *gcamdata.* https://github.com/JGCRI/gcamdata

Global Change Analysis Model. (n.d.). Joint Global Change Research Institute. https://gcims.pnnl.gov/modeling/gcam-global-change-analysis-model

Keppo, I., Butnar, I., Bauer, N., Caspani, M., Edelenbosch, O., Emmerling, J., Fragkos, P., Guivarch, C., Harmsen, M., Lefèvre, J., Gallic, T. L., Leimbach, M., McDowall, W., Mercure, J.-F., Schaeffer, R., Trutnevyte, E., & Wagner, F. (2021). Exploring the possibility space: Taking stock of the diverse capabilities and gaps in integrated assessment models. *Environmental Research Letters*, *16*(5), 053006. https://doi.org/10.1088/1748-9326/abe5d8

International Institute for Applied Systems Analysis. (2022). *message_ix*. https://github.com/iiasa/message_ix

Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., & Khorenzhenko, I. (2019). Towards agent-based integrated assessment models: Examples, challenges, and future developments. *Regional Environmental Change*, *19*(3), 747–762. https://doi.org/10.1007/s10113-018-1287-9

Leonelli, S. (2015). What counts as scientific data? A relational framework. *Philosophy of Science*, *82*(5), 810–821. https://doi.org/10.1086/684083

Leonelli, S. (2019). Data governance is key to interpretation: Reconceptualizing data in data science. *Harvard Data Science Review*, *1*(1). https://doi.org/10.1162/99608f92.17405bb6

Nikas, A., Doukas, H., & Papandreou, A. (2019). A detailed overview and consistent classification of climate-economy models. In H. Doukas, A. Flamos, & J. Lieu (Eds.), *Understanding Risks and Uncertainties in Energy and Climate Policy: Multidisciplinary Methods and Tools for a Low Carbon Society* (pp. 1–54). Springer International Publishing. https://doi.org/10.1007/978-3-030-03152-7_1

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., & van Vuuren, D. P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, *122*(3), 387–400. https://doi.org/10.1007/s10584-013-0905-2

Rissman, J., Bataille, C., Masanet, E., Aden, N., Morrow, W. R., Zhou, N., Elliott, N., Dell, R., Heeren, N., Huckestein, B., Cresko, J., Miller, S. A., Roy, J., Fennell, P., Cremmins, B., Koch Blank, T., Hone, D., Williams, E. D., de la Rue du Can, S., … Helseth, J. (2020). Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied Energy*, *266*, 114848. https://doi.org/10.1016/j.apenergy.2020.114848

van Beek, L., Hajer, M., Pelzer, P., van Vuuren, D., & Cassen, C. (2020). Anticipating futures through models: The rise of integrated assessment modelling in the climate science-policy interface since 1970. *Global Environmental Change*, *65*, 102191. https://doi.org/10.1016/j.gloenvcha.2020.102191

Wilson, C., Kriegler, E., van Vuuren, Guivarch, C., Frame, D., Krey, V., Osborn, T. J., Schwanitz, V. J., & Thompson, E. L. (2017, May). *Evaluating process-based integrated assessment models of climate change mitigation* (IIASA Working Paper No. WP-17-007). https://pure.iiasa.ac.at/14502

IEA. (2022). *World Energy Balances—Data product*. https://www.iea.org/data-and-statistics/data-product/world-energy-balances