Improving poverty and inequality modeling in climate research

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With climate change getting increasingly real and present, the risk of adverse impacts on vulnerable populations is growing. As governments seek more drastic action, policymakers are likely to seek quantification of climate change impacts and also the consequences of mitigation policies on these populations. Current models used in climate research have a limited ability to represent the poor and vulnerable, and the different dimensions along which they face these risks. Best practices need to be adopted more widely and new model features that incorporate social heterogeneity and different policy mechanisms also need to be developed. Increased collaboration between modelers, economists, and other social scientists could aid these developments.

We review the history and state of the art of models used in climate research, including Integrated Assessment Models (IAMs) and national studies, and those that model mitigation and climate change impacts. We assess how and to what extent they represent distributional impacts within countries. We argue that there is much scope to improve the representation of income distribution and poverty. Given the diversity of models, this endeavor can present fundamental challenges for some, but possibly require only incremental changes in others.

1. Why model poverty and inequality

Climate-related research has established firmly that different populations within countries are affected differently by climate change and climate mitigation policies, very often with the poor bearing the most drastic consequences [1–5]. Climate change affects poverty through many channels, such as through livelihoods, consumption, assets, health, and productivity [6,7]. Climate mitigation policies can generate income and price shocks, which in some cases can also increase health risks to the poor [8]. Climate mitigation technologies can also generate differential impacts on different income groups, a notable example being the extensive deployment of biomass for energy and its implications for food security [9,10]. In order to meet the Paris climate agreement goals of keeping warming below 2◦C above preindustrial levels, national pledges to reduce greenhouse gas (GHG) emissions need to be ramped up significantly [11]. Such ambitious climate policies may present greater risks to those in poverty [8]. Incorporating these impacts on poverty can make climate economic models more useful for national policymakers to evaluate climate policies and their impacts on social protection goals. These improvements would be timely, considering the recent attention to combating both social inequalities and climate change. While almost a billion people have putatively risen out of extreme income poverty (earning $1.90/day) [12], progress viewed through a broader lens of basic human development, or multidimensional poverty, is far less encouraging [13,14]. Multidimensional indicators recognize the multifaceted nature of human deprivations, whose patterns do not necessarily coincide with income deprivations. In the last few decades, income inequality within countries has also increased across most of the world [15]. Models that can assess income distributional impacts of climate change and policies, and assess poverty in its multiple dimensions, would provide policymakers with tools to more rigorously assess climate change and human development goals simultaneously.

The recognition of distributional concerns in climate research can be traced back to the nineties, the timeframe of the IPCC's first assessment reports [16,17]. The research gaps identified then have been repeated in subsequent IPCC assessments, showing they persist till today [4,5]. Many studies with countries or regions as units of analysis have concluded that poor countries are more vulnerable and have lower adaptive capacity to climate change[1–3]. Moreover, aggregate cost estimates mask significant differences across populations [18], and adaptive capacity is uneven within societies as well [19]. The IPCC's most recent Fifth Assessment Report (AR5) reflects much evolution in regional studies of climate impacts, but distributional impacts remain underexplored.

In general, while IAMs and macroeconomic models used in climate research have evolved from global outcomes towards increasing geographic detail [20], more models have to move beyond representing average regional effects to quantify and project distributional effects and their complexities in countries. Even global reduced form models that generate aggregate or regional statistics, such as the social cost of carbon, have different outcomes when they incorporate income inequality by assigning greater weight to damages at lower income levels [18,21–24]. These equity weights and the types of damage functions assumed can greatly influence decisions on when, how much, and where to mitigate GHG emissions [25,26]. Models that grapple more explicitly with these normative frameworks and their implications can better inform policymakers and their perceptions of what is fair, feasible and consistent with development policies. Some studies using global IAMs serve as examples of such enhancements, though they formulate policies for idealized global or regional policymakers [27–29].

With increasing attention given to adaptation, research gaps have broadened towards understanding the effects of adaptation decisions on poverty and income inequality [30]. The channels of climate impact on humans are inherently multi-faceted, such as human health vulnerabilities relating to clean water/sanitation, health care and education [4,6,19]. Models dealing with cost-benefit analyses of adaptation choices can better inform policymakers' decisions if they can quantify multidimensional poverty. Estimating future vulnerabilities to climate change also requires the construction of future socioeconomic scenarios that quantify future poverty and inequality. In order to present policy makers with the full range of options and consequences, we need approaches to estimate adaptation costs, barriers and opportunities in different countries and populations, and to develop comparable metrics to measure climate impacts.

2. State of the art

We organize this discussion by models that assess climate mitigation and those that assess climate change impacts. We also distinguish national level models from global level models. For the latter, we make a distinction between IAMs for cost-benefit analysis (CBA-IAMs), which tend to be more stylized, and IAMs with a predominantly mitigation framing that are more detailed and process oriented (Process-IAM). Models that analyze the effects of climate mitigation policies both at the national and global levels can be grouped into general equilibrium (GE) and partial equilibrium (PE, often bottom-up energy system models). Climate change impacts models tend to be national or local studies that sometimes represent the macroeconomy, or global CBA-IAMs. The model-types and references of examples mentioned in this section are summarized in Table 1.

In the realm of climate mitigation, many national studies assess the distributional impacts of mitigation using general equilibrium approaches, mostly for the US and Europe [31–42], though increasingly also for developing countries [32,43–48]. Methodologically, the literature reveals a variety of stages towards including distributional impacts on households. With regard to how households are represented, approaches include simply imposing distributions [49,50], using microsimulation models (see Table 1) [40,51,52], and representing multiple household types within models [31,53,54]. Some of these approaches are being applied with global Process-IAMs as well [10,55,56]. However, the norm for studies in this realm continues to be the use of single representative households [54].

Increasing household heterogeneity in modeling tools is only the first step. For meaningful results, models also need to incorporate other agents and the relevant dynamics that influence the distributional impacts of climate policies and climate change impacts on households. For instance, the role of the government (which is usually modelled quite stylistically in CGEs) is often decisive for the distributional impacts of policies [40]. The policy instruments used to represent climate policies are typically limited to the simulation of economy-wide carbon taxes [57,58]. Many studies assess the interaction of climate policies with social protection policies, such as revenue recycling. However, social protection policies may also differ in developing countries that lack well developed income tax systems.

Other relevant dynamics that affect the distributional impacts of climate policies include the evolution of the structure of labor and capital markets over time. Without distinguishing the relevant labor markets in a CGE model, sectoral shifts in employment and wages from mitigation policies, for instance, cannot be analyzed. Structural changes in labor and capital market shares also affect the non-economic impacts of climate change and potential response policies. For instance, the number of workers exposed to heat stress is likely to much lower in a high-productive, capital intensive, robotized world than in a low-productive, labor-intensive, impoverished economy. The aggregate impacts on GDP might (or might not) be comparable, but the distributional consequences of heat stress and response policies should be very different.

In bottom-up energy models and global Process-IAMs of this style, the analysis of distributional impacts is often limited to consumption of energy by households. Disaggregation of households into several groups or many representative households has been implemented for developed [33,42,59,60] and developing countries [61–65] with varying levels of detail. Process-IAMs distinguish multiple household categories within the IAM itself [66,67] or use separate models to disaggregate energy use from a representative household within the global IAM [62]. These models have been used to analyze global access to electricity [68] and tradeoffs between climate policy and energy access [8]. However, by focusing only on household energy price impacts, these models can only analyze the changes in energy consumption, while ignoring any changes in income. They have very limited ability to represent the interlinkages and cascading effects between particular sectors and the rest of the economy, let alone how these effects are distributed across households.

With respect to climate change impacts, studies that quantify inequality or (multidimensional) poverty are rare (with the exception of a recent World Bank study [6,69]). Many impacts and vulnerability studies rely on present-day income distributions and poverty levels to assess future vulnerability [70,71]. Even if they do use future socioeconomic scenarios, studies typically adopt simple rules such as constant income distributions, or poverty levels indexed to GDP [10,19]. A patchwork of national studies that uses a more complete accounting of income and/or consumption impacts [51,56,72–74] exists, but differences in measures and approaches makes it difficult to draw broader conclusions or comparisons. Moreover, climate change can affect households in different ways, through shifts in sectoral employment, through price changes of essential goods or through the destruction of assets. Some attempts to include such dynamics in global Process-IAMs exist [10,50,52,53], but these are early steps of development.

Integrated Assessment Models for cost-benefit analysis (CBA-IAMs) produce global economic assessments of climate change impacts. In these studies, distributional weights have long been used to represent equity across generations or regions [4]. Such weighting strongly influences the valuation of future impacts of climate change [18,25,26] or the valuation of impacts that take place outside a particular country [22]. Recently, we have seen experiments with the use of distributional weights within generations, to represent inequality aversion between countries [21,24] or across sub-national income groups [18]. A limitation in these studies is the strong assumption of either static present-day subnational income distributions or convergence between countries [21,24,28].

In summary, although the above discussion cites a wealth of literature on distributional impacts, the large majority of climate-related models do not consider any distributional impacts. Moreover, all the methods discussed here have important shortcomings that need to be addressed. For instance, for a full account of the distributional impacts of climate policies and climate change impacts, both the income and consumption aspects of households need to be represented and the relevant determinants of changes on either side need to be included. However, whereas partial equilibrium models generally include higher levels of heterogeneity (especially at the global level), they only focus on changes in consumption, and while general equilibrium models include both consumption and income they are often more aggregated and omit relevant economic dynamics that shape future income distribution development. More broadly, the existing approaches narrowly focus on economic inequality, whereas climate change impacts may manifest through multi-faceted poverty. Not all approaches can include such a broad scope, but national-level models in particular can better inform policy makers with a broader focus.

3. Drawing from economics

In better representing income inequality dynamics in climate economic models, it seems logical to draw from existing theories of income distribution in economics. In just the last few years, several publications [75–79] seek to explain global trends in income inequality. However, even among economists there are multiple views, but no single unified theory, that explain income inequality. Previous theories of income distribution offer building blocks of explanatory mechanisms, but provide no consensus on their integration [80]. These building blocks relate to the productivity, distribution, and to the accumulation of, and the returns to, factors of production (e.g., capital and labor). The recent body of literature adds, among other things, empirical insights on the importance of government structure and policy in explaining regional differences in the evolution of income inequality [75,76,79]. However, there are no generally accepted theories relating these drivers to inequality, let alone ways to forecast their future evolution. The approach to drawing from this literature may therefore have to be experimental. Rather than aiming to incorporate dynamics, suitable models can parameterize some of these drivers, so that at least scenarios can be constructed to represent different assumptions, such as variable capital shares of income, or redistributive mechanisms.

In the field of poverty measurement, multidimensional indicators, such as the Multidimensional Poverty Index (MPI) [14], have gained attention as alternatives to income-based measures. The MPI focuses on education, health (including food) and living conditions, such as access to water, electricity and sanitation. Others define a more comprehensive a set of indicators of human well-being, only some of which may be relevant for any particular application [81]. The value of these indicators is that they provide a basis for climate impact studies (and to a lesser extent for climate policy studies) to quantify impacts in non-monetary but yet standardized terms that can enable comparisons across different types of impacts that have similar types of outcomes. The challenge is that there are no established indicators or practices. Process-IAMs, which may already include the evolution of these other crucial dimensions, are well suited to broaden their objective functions to include these non-monetary outcomes, and examine trade-offs between them.

4. Moving forward

Different types of models, depending on their objective and geographic scale, may require different approaches to enhance the representation of poverty and inequality (see Figure 1). We discuss these in the sequence of our suggested future directions shown in Figure 1, by column from left to right. This list of suggestions is not meant to be exhaustive, but rather highlights examples of future directions that apply to different models.

Figure 1: State of the art and future research directions in representing poverty/inequality in models for climate research. CBA-IAM: Global IAM, cost-benefit analysis. Process-IAM: Process-oriented IAMs with mitigation framing. CGE: Computable general equilibrium.

1. In the realm of impact measurement, dimensions beyond income need to be better represented where possible, and where not, multiple income thresholds should be used. This is most relevant for national models of climate impacts, or global Process-IAMs of mitigation pathways that already include income distribution and multiple poverty-related variables. Multidimensional poverty metrics can be used to quantify the change in poverty headcount or gap from different types of climate impacts that may not all be monetizable, such as access to clean water, or adequate nourishment. This broadening of metrics has the added benefit of enabling comparisons across the Sustainable Development Goals, which include such targets. In the long run, deepening integrated research across scales, by examining local climate impacts alongside other national drivers of poverty, would better represent climate as a threat multiplier made that compounds other poverty risks [19].
2. Models that represent climate impacts as damage functions, such as global CBA-IAMs, can create formulations that parameterize regions and their income distributions and incorporate equity weights, which then deepens the assessment of equity more explicitly in solutions for climate policy. As discussed earlier, some examples of this exist, but these need to become

standard practice. Furthermore, more research on empirical estimates of regional damages and their distribution can help calibrate these damage functions.

3. Moving from a single representative household to multiple household groups is possible in any model type. It can serve as a foundational step towards building the capability to examine policy impacts that depend on household characteristics. However, this step entails increases in data needs that would expand with the extent of household disaggregation. Besides increasing the number of household types, some modelers have developed microsimulation models or worked with stylized distributions of income and consumption in future scenarios. These exceptions need to become the norm where feasible.
4. Models that already incorporate income distributions, but in static form, can extend their capability to examine climate (or mitigation) impacts under different scenarios of future income inequality by constructing scenarios of future income convergence and divergence, both between and within countries. Such scenarios can consist of stylized assumptions, or incorporate economic dynamics, to the extent feasible [49,69,82]. These improvements are relevant to both global IAMs and national economic models.
5. Incorporating multiple channels of impact on poverty and inequality would be more involved, and require incremental steps in macroeconomic models that already model multiple household groups. The channels we have identified are income, consumption, and assets. There are a few examples of climate impact studies, typically agriculture economic models, which incorporate both consumption- and income-side effects on households. This needs to become the standard for economic impact studies. Capturing income effects requires modeling labor productivity, which affects income directly through returns to labor and indirectly through macroeconomic effects of changes in overall labor productivity. Another step forward is to represent changes to capital assets, which are vulnerable to extreme events and affect future income or consumption streams. This may not apply to certain types of macroeconomic growth-models that use fixed capital/labor shares in production functions.
6. The role of government in shaping future inequality and in formulating responses to climate change is so dominant that models need to move towards incorporating policy mechanisms. Among economic models that do represent government policies, a broader range of policies for both climate mitigation and social protection would better reflect real world institutions, especially in developing economies that do not have well developed income tax systems.
7. Partial equilibrium and bottom-up energy models, if they include household heterogeneity, can be enhanced by exogenous assessment of income effects, or of specific relevant linkages that

affect the poor, such as the air pollution and health impacts from energy transitions on different income groups [8]. This could be an important addition to several global Process-IAMs as well.

Bringing into climate economic models new features of the real world – that of social heterogeneity – introduces additional sources of uncertainty in model output, as well as the need to calibrate new model parameters to the real world. Empirical studies of climate impacts and damages on poverty and on inequality can help test and refine new model features. Monte Carlo simulations over large scenario spaces associated with specific sets of parameters can help characterize the range of uncertainty attributable to these model enhancements.

These changes will be challenging. They require not just analytical advances, but also building bridges across research communities, to explore incorporating evolving theories on income inequality from economics into climate economic models. While there are a few examples that can lead the way, in general, these exceptions need to become the norm, so that the research community can keep up with the pace required of policymakers to combat climate change. Data limitations in understanding the mechanisms that drive income distribution and in empirical estimates of climate impacts exacerbate this challenge. This will require more interaction between research groups working on global models and local research communities that conduct empirical studies or work with national models.

Table 1: Representation of household heterogeneity in state-of-the-art climate economic models. Models are classified by their scale (national, global), scope (single sector, partial or full economy) and objective (partial equilibrium, general equilibrium (CGE), cost-benefit analysis (CBA)), with exemplar citations. Microsimulation: models that disaggregate aggregate outcomes to households based on empirical analyses of individual characteristics.

Model Type	➔ **Increasing Complexity of Social Heterogeneity**			
	Single HH	**Prescribed distribution**	**Multiple HH-types**	**Microsimulation**
National, Single sector	Most common	Mitigation: [59,61]	Mitigation: [35,63,67,83]	Mitigation: [60,62,64] Impacts: [84]
National, CGE	Most common		Mitigation: [31,32,34,36,39,43–46,73]	Mitigation: [33,40,46–48,65] Impacts: [51,72]
Global Process-IAM, partial equilibrium	Most common		Mitigation: [66]	Mitigation: [8]
Global Process-IAM, CGE	Most common	Impacts: [10,50]	Impacts: [53]	Mitigation: [56,85] Impacts: [52]
Global CBA-IAM	Most common	Mitigation[86] Impacts:[18,21,24,86]		

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Author Contributions

NR and BvR conceptualized, researched and wrote the paper. VB and KR provided conceptual inputs.

REFERENCES

1. De Cian, E., Hof, A. F., Marangoni, G., Tavoni, M. & van Vuuren, D. P. Alleviating inequality in climate policy costs: an integrated perspective on mitigation, damage and adaptation. *Environ. Res. Lett.* **11,** 74015 (2016).
2. Mendelsohn, R., Dinar, A. & Williams, L. The distributional impact of climate change on rich and poor countries. *Environ. Dev. Econ.* **11,** 159 (2006).
3. Tol, R. S. J., Downing, T. E., Kuik, O. J. & Smith, J. B. Distributional aspects of climate change impacts. *Glob. Environ. Chang.* **14,** 259–272 (2004).
4. Edenhofer, O. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Field, C. B. et al.) 35–94 (Cambridge University Press, 2014).
5. Field, C. B. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Field, C. B. et al.) 35–94 (Cambridge University Press, 2014).
6. Hallegatte, S. *et al. Shock waves: Managing the impacts of climate change on poverty*. (2016). doi:10.1596/978-1-4648-0673-5
7. O'Neill, B. C. *et al.* A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Clim. Change* **122,** 387–400 (2014).
8. Cameron, C. *et al.* Policy trade-offs between climate mitigation and clean cook-stove access in South Asia. *Nat. Energy* **1,** 15010 (2016).
9. Kline, K. L. *et al.* Reconciling food security and bioenergy: priorities for action. *GCB Bioenergy* **9,** 557–576 (2017).
10. Hasegawa, T. *et al.* Consequence of Climate Mitigation on the Risk of Hunger. *Environ. Sci. Technol.* **49,** 7245–7253 (2015).
11. Rogelj, J. *et al.* Paris Agreement climate proposals need a boost to keep warming well below 2 °C. *Nature* **534,** 631–639 (2016).
12. World Bank. Poverty Overview. Available at: http://www.worldbank.org/en/topic/poverty/overview. (Accessed: 5th November 2016)
13. Reddy, S. & Lahoti, R. $1.90 per day: what does it say? 1–28 (2015). Available at: https://reddytoread.files.wordpress.com/2015/10/wbpovblogoct6final1.pdf.
14. Alkire, S. & Santos, M. E. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. *World Dev.* **59,** 251–274 (2014).
15. Milanovic, B. *Worlds apart: measuring international and global inequality*. (Princeton University Prss, 2005).
16. IPCC. *Climate Change 1995: Economic and Social Dimensions of Climate Change. Contribution of the Working Group III to the Second Assessment Repoert of the IPCC*. (1996).
17. Thomas C . Schelling. Some Economics of Global Warming. *Am. Econ. Rev.* **82,** 1–14 (1992).
18. Dennig, F., Budolfson, M. B., Fleurbaey, M., Siebert, A. & Socolow, R. H. Inequality, climate impacts on the future poor, and carbon prices. *Proc. Natl. Acad. Sci.* **112,** 15827–15832 (2015).
19. Olsson, L. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change* (eds. Field, C. B. et al.) 793–832 (Cambridge University Press, 2014).
20. Krey, V. Global energy-climate scenarios and models: a review. *Wiley Interdiscip. Rev. Energy Environ.* **3,** 363–383 (2014).
21. Anthoff, D., Hepburn, C. & Tol, R. S. J. Equity weighting and the marginal damage costs of climate change. *Ecol. Econ.* **68,** 836–849 (2009).
22. Anthoff, D. & Tol, R. S. J. On international equity weights and national decision making on climate change. *J. Environ. Econ. Manage.* **60,** 14–20 (2010).
23. Adler, M, D Anthoff, V Bosetti, G Garner, K Keller, and N. T. Priority For The Worse Off And The Social Cost Of Carbon. *Nat. Clim. Chang.* (2017).
24. Anthoff, D. & Emmerling, J. *Inequality and the Social Cost of Carbon*. (2016).
25. Stanton, E. A. Negishi welfare weights in integrated assessment models: The mathematics of global inequality. *Clim. Change* **107,** 417–432 (2011).
26. Stanton, E. a., Ackerman, F. & Kartha, S. Inside the integrated assessment models: Four issues in climate economics. *Clim. Dev.* **1,** 166 (2009).
27. Anthoff, D. Optimal Global Dynamic Carbon Abatement. *Univ. California, Berkeley* 1–28 (2011).

28. Budolfson, M., Siebert, A. & Spears, D. Optimal climate policy and the future of world economic development. *World Bank Econ. Rev.* (2017).
29. Budolfson, M. B. & Dennig, F. in *Handbook on the economics of climate change* (eds. Chichilnksky, G., Sheeran, K. & A. Rezai) (Edward Elgar Press, 2017).
30. Chambwera, M. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change* (eds. Field, C. B. et al.) 945–977 (Cambridge University Press, 2014).
31. Rausch, S., Metcalf, G. E. & Reilly, J. M. Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Econ.* **33, Supple,** S20–S33 (2011).
32. Liang, Q. M. & Wei, Y. M. Distributional impacts of taxing carbon in China: Results from the CEEPA model. *Appl. Energy* **92,** 545–551 (2012).
33. Callan, T., Lyons, S., Scott, S., Tol, R. S. J. & Verde, S. The distributional implications of a carbon tax in Ireland. *Energy Policy* **37,** 407–412 (2009).
34. Siriwardana, M., Meng, S. & McNeill, J. *The Impact of a Carbon Tax on the Australian Economy : Results from a CGE Model*. *Business, Economics and Public Policy Working Papers* (2011).
35. Bureau, B. Distributional effects of a carbon tax on car fuels in France. *Energy Econ.* **33,** 121–130 (2011).
36. Rausch, S. & Schwarz, G. A. Household heterogeneity, aggregation, and the distributional impacts of environmental taxes. *J. Public Econ.* **138,** 43–57 (2016).
37. Williams, R. C., Gordon, H., Burtraw, D., Carbone, J. C. & Morgenstern, R. D. *The initial incidence of a carbon tax across income groups*. (2014).
38. Mathur, A. & Morris, A. C. Distributional effects of a carbon tax in broader U. S. fiscal reform. *Energy Policy* **66,** 326–334 (2014).
39. Combet, E., Ghersi, F. F., Hourcade, J.-C. & Théry, D. in *Critical Issues in Environmental Taxation* (eds. Dias Soares, C., Milne, J., Ashiabor, H., Dekete- laere, K. & Kreiser, L.) 277–295 (Oxford University Press, 2010).
40. Buddelmeyer, H., Hérault, N., Kalb, G. & van Zijll de Jong, M. Linking a Microsimulation Model to a Dynamic CGE Model: Climate Change Mitigation Policies and Income Distribution in Australia. *Int. J. Microsimulation* **5,** 40–58 (2012).
41. Sterner, T. Distributional effects of taxing transport fuel. *Energy Policy* **41,** 75–83 (2012).
42. Cullenward, D., Wilkerson, J. T., Wara, M. & Weyant, J. P. Dynamically estimating the distributional impacts of U.S. climate policy with NEMS: A case study of the Climate Protection Act of 2013. *Energy Econ.* **55,** 303–318 (2016).
43. Durand-Lasserve, O., Campagnolo, L., Chateau, j. & Dellink, R. *Modelling of distributional impacts of energy subsidy reforms: an illustration with Indonesia*. (OECD, 2015).
44. Naranpanawa, A. & Bandara, J. S. Poverty and growth impacts of high oil prices: Evidence from Sri Lanka. *Energy Policy* **45,** 102–111 (2012).
45. Yusuf, A. A. & Resosudarmo, B. P. On the distributional impact of a carbon tax in developing countries: the case of Indonesia. *Environ. Econ. Policy Stud.* **17,** 131–156 (2015).
46. Coxhead, I., Wattanakuljarus, A. & Nguyen, C. V. Are Carbon Taxes Good for the Poor? A General Equilibrium Analysis for Vietnam. *World Dev.* **51,** 119–131
47. Dartanto, T. Reducing fuel subsidies and the implication on fiscal balance and poverty in Indonesia: A simulation analysis. *Energy Policy* **58,** 117–134
48. Essama-Nssah, B. *et al. Economy-wide and Distributional Impacts of an Oil Price Shock on the South African Economy*. (World Bank, 2007).
49. Van der Mensbrugghe, D. Shared Socio-economic pathways and global income distribution. in *18th Annual Conference on Global Economic Analysis* (GTAP, 2015). doi:https://www.gtap.agecon.purdue.edu/resources/download/7554.pdf
50. Sánchez, M. V. & Cicowiez, M. Trade-offs and Payoffs of Investing in Human Development. *World Dev.* **62,** 14–29
51. Hertel, T. W., Burke, M. B. & Lobell, D. B. The poverty implications of climate-induced crop yield changes by 2030. *Glob. Environ. Chang.* **20,** 577–585 (2010).
52. Bussolo, M., De Hoyos, R. E. & Medvedev, D. Economic Growth and Income Distribution: Linking Macro-economic Models with Household Survey Data at the Global Level. *Int. J. Microsimulation* **3,** 91–103 (2010).
53. Bouet, A., Estrades, C. & Laborde, D. *Households heterogeneity in a global CGE model: an illustration with the MIRAGE-HH (MIRAGE-HouseHolds) model.* (University Montesquieu-Bordeaux IV, 2013).
54. van Ruijven, B. J., O'Neill, B. C. & Chateau, J. Methods for including income distribution in global CGE models for long-term climate change research. *Energy Econ.* **51,** 530–543 (2015).

55. Melnikov, N. B., O'Neill, B. C., Dalton, M. G. & Van Ruijven, B. J. Downscaling heterogeneous household outcomes in dynamic CGE models for energy-economic analysis. *Energy Econ.* **65,** 87–97 (2017).
56. O'Neill, B. C. *et al.* Global demographic trends and future carbon emissions. *Proc. Natl. Acad. Sci.* **107,** 17521–17526 (2010).
57. Burke, M. *et al.* Opportunities for advances in climate change economics. *Science (80-.).* **352,** 292–293 (2016).
58. Somanathan, E. *et al.* in *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Edenhofer, O. et al.) (Cambridge University Press, 2014).
59. Feng, K. *et al.* Distributional Effects of Climate Change Taxation: The Case of the UK. *Environ. Sci. Technol.* **44,** 3670–3676 (2010).
60. Chingcuanco, F. & Miller, E. J. A microsimulation model of urban energy use: Modelling residential space heating demand in ILUTE. *Comput. Environ. Urban Syst.* **36,** 186–194 (2012).
61. Jiang, Z. & Shao, S. Distributional effects of a carbon tax on Chinese households: A case of Shanghai. *Energy Policy* **73,** 269–277 (2014).
62. Ekholm, T., Krey, V., Pachauri, S. & Riahi, K. Determinants of household energy consumption in India. *Energy Policy* **38,** 5696–5707 (2010).
63. Rao, N. D. Distributional impacts of climate change mitigation in Indian electricity: The influence of governance. *Energy Policy* **61,** 1344–1356 (2013).
64. Howells, M. I., Alfstad, T., Victor, D. G., Goldstein, G. & Remme, U. A model of household energy services in a low-income rural African village. *Energy Policy* **33,** 1833–1851 (2005).
65. Hussein, Z., Hertel, T. & Golub, A. Climate change mitigation policies and poverty in developing countries. *Environ. Res. Lett.* **8,** 35009 (2013).
66. Daioglou, V., van Ruijven, B. J. & van Vuuren, D. P. Model projections for household energy use in developing countries. *Energy* **37,** 601–615 (2012).
67. van Ruijven, B. J. *et al.* Model projections for household energy use in India. *Energy Policy* **39,** 7747–7761 (2011).
68. Pachauri, S. *et al.* Pathways to achieve universal household access to modern energy by 2030. *Environ. Res. Lett.* **8,** 24015 (2013).
69. Hallegatte, S. & Rozenberg, J. Climate change through a poverty lens. *Nat. Clim. Chang.* **7,** 250–256 (2017).
70. Preston, B. L., Yuen, E. J. & Westaway, R. M. Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. *Sustain. Sci.* **6,** 177–202 (2011).
71. van Ruijven, B. J. *et al.* Enhancing the relevance of Shared Socioeconomic Pathways for climate change impacts, adaptation and vulnerability research. *Clim. Change* **122,** 481–494 (2014).
72. Ahmed, S. A. *et al.* Climate volatility and poverty vulnerability in Tanzania. *Glob. Environ. Chang.* **21,** 46–55 (2011).
73. Mideksa, T. K. Economic and distributional impacts of climate change: The case of Ethiopia. *Glob. Environ. Chang.* **20,** 278–286 (2010).
74. Brooks, N., Adger, W. N. & Kelly, P. M. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Glob. Environ. Chang.* **15,** 151–163 (2005).
75. Stiglitz, J. E. The Origins of Inequality, and Policies to Contain It. *Natl. Tax J.* **68,** 425–448 (2015).
76. Atkinson, A. B. *Inequality: what can be done*. (Harvard University Press, 2015).
77. Bourguignon, F. *The globalization of inequality*. (Princeton University Prss, 2015). doi:10.1017/CBO9781107415324.004
78. Piketty, T. *Capitalism in the 21st century*. (Harvard University Press, 2014).
79. Robinson, J. A., Acemoglu, D. & Robinson, J. A. *Democracy , Redistribution and Inequality*. (2013).
80. Atkinson, A. B. & Bourguignon, F. in *Handbook of Income Distribution* (eds. Atkinson, A. B. & Bourguignon, F.) **1,** 1–58 (2000).
81. Rao, N. D. & Min, J. Decent living standards: material requirements for human well-being. *Soc. Indic. Res.* (2017). doi:10.1007/s11205-017-1650-0
82. Dellink, R., Chateau, J., Lanzi, E. & Magné, B. Long-term economic growth projections in the Shared Socioeconomic Pathways. *Glob. Environ. Chang.* 1–15 (2015). doi:10.1016/j.gloenvcha.2015.06.004
83. Oladokun, M. G. & Odesola, I. A. Household energy consumption and carbon emissions for sustainable cities – A critical review of modelling approaches. *Int. J. Sustain. Built Environ.* **4,** 231–247 (2015).
84. Jacoby, H., Rabassa, M. & Skoufias, E. Distributional Implications of Climate Change in India. *Am. J. Agric. Econ.* **97,** 1–22 (2014).
85. Melnikov, N. B., O'Neill, B. C. & Dalton, M. G. Accounting for household heterogeneity in general equilibrium economic growth models. *Energy Econ.* **34,** 1475–1483 (2012).

86. Budolfson, M., Dennig, F., Fleurbaey, M., Siebert, A. & Socolow, R. H. *The Comparative Importance for Optimal Climate Policy of Discounting , Inequalities , and Catastrophes*. (2016).