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Abstract

Feedbacks within the climate-economy system are complex. The research analyzing the relationship between human activities and the climate is considerable, with particular focus on intra-system feedback effects: environmental tipping points, and climate-triggered social tipping points, like migration, to a lesser extent (Robert Kopp et al., 2016; Kees van Ginkel et al., 2018). Due to their cross-disciplinary nature (Angela Guerrero et al., 2018), two-way interactions between the environment and society, whereby movement in either system can trigger inter-system feedbacks (Steven Lade et al., 2013; Johanna Yletyinen et al., 2019) as humans respond to a changing environment thereby further changing the environment, have only recently received attention by a growing inter-disciplinary research community. With the aim of improving climate policy and its tools, such as the social cost of carbon, we describe these social-ecological system (SES) feedbacks and place them in the existing taxonomy for tipping points applied by mainstream climate-economy models. Drawing lessons from SES research and related interdisciplinary literatures, we discuss the value of and method by which to modify social-cost integrated assessment models (SC-IAMs), like Nordhaus' DICE. As it is critical that climate policy include these risks to the stability of the climate-economy system, we conclude with a research agenda for the identification, quantification, and integration of climate-society feedbacks into SC-IAMs.

Key Words: Social-ecological systems; feedbacks; integrated assessment models; social cost of carbon

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1. Introduction

The interaction between climate change and human societies is complex and involves an array of feedbacks within and across social and environmental systems. In recent years, significant progress has been made in understanding feedbacks within relevant systems (Kopp et al., 2016; van Ginkel et al., 2018) but feedbacks *between* environmental and social systems remain relatively understudied (Lade et al., 2013; Yletyinen et al., 2019; Guerrero et al., 2018). Even the best existing models to understand climate risks and inform climate policy making (Richard Revesz et al., 2017) fail to incorporate these feedbacks, which may lead to consistent understatement of the value of mitigation and adaptation investments (Peter Howard & Michael Livermore, 2019).

The planet Earth is essentially one large social-ecological system, with human activities affecting and being affected by the environment. Humans have always been susceptible to the vagaries of nature: from time immemorial, droughts, floods, storms, pestilence, earthquakes, fires, volcanic eruptions, and tsunamis have had profound influences on human development. In turn, humans have affected the environmental systems around them through hunting, extraction and use of resources, and pollution and waste disposal (Jonathan Donges et al., 2018; Kopp et al., 2016). At least since the dawn of the industrial revolution, humans have also influenced the climate system though greenhouse gas emissions, an effect that has grown larger with time (IPCC, 2014).

Critical feedback effects exist within and between the Earth's various systems. Formally, a feedback occurs when the output of a system is also an input to that system. An example of a positive, self-enforcing feedback in the climate system is the release of methane from melting permafrost: the increase in methane is both an output of the climate system as well as an input. Negative, self-limiting feedbacks also exist, as when carbon fertilization leads to an increase in the carbon sequestration potential in forests. Social-ecological feedbacks arise when environmental change affects human behavior in ways that in turn impact those same environmental systems. In the context of climate change, rising temperatures and their various impacts will change human behavior, including the emissions of greenhouse gases, which then affect the climate system, which in turn further impacts human behavior (Brian Beckage et al., 2018).

Social-cost integrated assessment models (NAS, 2017), like William Nordhaus's Dynamic Integrated Climate Economy (DICE) model, are an example of an early attempt to model certain social-ecological feedbacks. Social-cost IAMs (SC-IAMs) were designed to capture the steps in the climate and economic systems that translate a marginal unit of carbon dioxide emissions into economic damages. These models connect a simple climate model to a simple economic model to capture an intersystem feedback: human caused greenhouse gas emissions feed back into the social system as climate damages reduce future returns on investment and capital stores (William Nordhaus, 1994; Maja Schlüter et al., 2017; Katherine Calvin & Ben Bond-Lamberty, 2018; Beckage et al., 2018). Despite this early recognition of social-ecological feedbacks, these models do not include many other potential social-ecological feedbacks.

Capturing relevant feedbacks is essential to accurate climate-economy modeling, a reality that was recently recognized by the National Academy of Sciences (2017). In this paper, we survey the current state of knowledge concerning social-ecological feedbacks in the climate system (i.e. climate-society feedbacks), propose avenues of future research, and discuss how to integrate climate-society feedbacks into SC-IAMs and climate policy making.[1] Our goal is to spur modelers to incorporate climate-society feedbacks into the next generation of climate-economy models and to help galvanize the growing cross-disciplinary research community that is focused on this important class of human-environment interactions.

In recent years, several multi-disciplinary subfields have arisen that are focused on the relationship between human and environmental systems (Schlüter et al., 2012; Detlef van Vuuren et al., 2012; Roelof Boumans et al., 2015). This work goes by several different names, including Social Ecological System (SES) modeling (Lade et

[1] Social-ecological system feedbacks are missing from many other mainstream environmental, economic, and climate models (Donges et al., 2018; Palmer & Smith, 2014; van Vuuren et al., 2012; Kelly & Kolstad, 1999; Weyant, 2017; van Vuuren et al., 2012; Schlüter et al., 2012). This paper focuses on climate-economy modeling and climate-society feedbacks with a particular focus on SC-IAMs and substitute and complementary (IAM) approaches.

al., 2013; Hendrik Santoso Sugiarto et al., 2015; Manjana Milkoreit et al., 2018; Yletyinen et al., 2019); Coupled Human and Natural Systems (CHANs) (Li An, 2012; An et al., 2014);[2] and integrated human-earth system modeling (Calvin & Bond-Lamberty, 2018; Paul Palmer & Matthew Smith, 2014; van Vuuren et al., 2012). One of the primary goals of this paper is to review this rapidly growing literature (Guerrero et al., 2018; Calvin & Bond-Lemberty, 2018) to summarize the existing state of knowledge on climate-society feedbacks.

Moving forward, we provide several suggestions for future work in identifying, analyzing, and modeling climate-society feedbacks. We propose several guiding principles that are grounded in a desire to focus research on ways that will be best suited to inform climate policy making. First, because climate-society feedbacks add to model complexity, there is a need to balance completeness with parsimony. Accordingly, attention should be placed on larger feedback effects, those that are likely to matter on human time scales, and key system nodes.[3] Second, because emergent properties that arise in flexible models of climate-society feedbacks may or may not map onto real world phenomenon, empirical testing of these model prediction is needed for confirmation. Third, modifying SC-IAMs to include simple, reduced-form feedback effects that have strong theoretical grounding and, where possible, empirical support is a robust and well-justified approach to incorporating climate-society feedbacks into policy modeling that is likely to inspire the confidence of decision makers.

The research agenda that we propose will necessarily rely on interdisciplinary teams that can identify potential feedback loops; develop the data necessary to test the existence of each step in these causal loops; estimate the magnitude and timing of the overall feedback; identify the appropriate mathematical representation; and develop and test early warning signals. This work is critical, given the climate-economic community's almost exclusive focus on environmental tipping points. Some climate-society feedbacks may have dampening effects—as when climate damages turn public opinion towards climate action (R.A. Bentley et al., 2014; Kopp et al., 2016; J. David Tàbara et al., 2018). But positive feedbacks within the climate-society system may also exist (Tàbara et al., 2018; Howard & Livermore, 2019), and inter-system feedbacks can be particularly dangerous for a variety of reasons, including mismatch between systems and management institutions; spatial and temporal separation between actions and consequences; and the difficulty of identifying and monitoring effects in multiple systems (Lade et al., 2013; Yletyinen et al., 2019).

The remainder of this paper is structured as follows. First, we describe social-ecological systems feedbacks and place them in an existing taxonomy of feedbacks. Second, we draw lessons from the existing SES, CHANS, and related interdisciplinary literatures and discuss the value of modifying SC-IAMs to include climate-society feedbacks. Next, we propose a methodology for integrating climate-society feedbacks more generally into William Nordhaus's Dynamic Integrated Climate Economy (DICE) model, the most prominent SC-IAM and reduced-form IAM more generally. Finally, we conclude by laying out a research agenda for climate-society systems with a particular focus on integrating economic research into this broader research program.

2. The Climate-Economy System is a Social-Ecological System

Social-ecological systems involve strong interactions between underlying environmental/ecological and human/social subsystems and cannot be accurately modeled without explicitly representing these interactions (Schlüter et al., 2012). Complex characteristics that arise from interactions and feedbacks within and between subsystems include co-evolutionary dynamics, path dependency, heterogeneity, adaptivity, non-linear dynamics, regime shifts, self-organization, cross-scale interactions, and emergent properties. This complexity may be increasing over time with developments in human society (Noa Avriel-Avni & Jan Dick, 2019), and interacts with the deep uncertainties associated with some social-ecological systems. Although modeling social-ecological system necessarily requires that complex features be accounted for, these same features can also lead to model intractability (An et al., 2014).

[2] CHANS are also referred to as Coupled Natural and Human (CNH) systems and human-environmental systems (An et al., 2014).

[3] Existing evidence indicates that SES feedbacks can be small to large in impact highlighting a range from negligible to equivalent to switching RCP scenarios (Calvin & Bond-Lemberty, 2018).

The climate-society system is an example of a large, complex social-ecological system: human behavior is a major driver of climate change and climate change greatly impacts humans, leading to interactions and feedbacks between human and ecological subsystems. In traditional climate-economy models, these inter-system feedback effects have been largely ignored. Thus, traditional feedback/tipping point taxonomies and integrated assessment models used in climate-economics omit these feedbacks.

2.1 Environmental Feedbacks, Social Feedbacks, and Climate-Society Feedbacks

There are three general categories of feedbacks that are relevant for modeling the climate-economy system. The first category are feedbacks *within* the climate system—we refer to these as *environmental feedbacks*. An example of an environmental feedback is increasing temperature causing permafrost melt, which releases methane gas, which leads to increasing temperature. The second category are feedbacks *within* social systems—we refer to these as *social feedbacks*. An example of a social feedback is shock to economic growth, which leads to social unrest, which undermines economic growth. The final category are *climate-society feedbacks*, which occur when there are feedbacks *across* environmental and social systems. An example of a climate-society feedback is climate change damages that reduce economic growth, which leads to fewer greenhouse gas emissions, which reduces future climate change. All three categories of feedbacks can be positive (i.e., self-reinforcing) or negative (i.e., dampening).[4]

The scientific literature documents a variety of positive feedback effects within the climate system, which in some cases can result in large regime shifts. Some of these tipping elements exhibit network feedback effects that can result in rapid non-linear regime shifts. Kopp et al. (2016) identifies several such abrupt environmental tipping points within the environmental subsystem. These include disruptions to atmosphere/ocean circulation, the cryosphere, or major ecosystems. Abrupt environmental tipping points can lead to runaway climate change through positive feedback effects including release of greenhouse gases or reduction of albedo. Additionally, Kopp et al. (2016) identifies four social tipping points triggered by climate change: large climate damages can trigger *conflict/development traps* whereby loss of GDP leads to increased social and political conflict, further undermining GDP; *climate-induced migration* to a particular destination may "pull" additional migration via social networks; *environmental policy* may be influenced by climate impacts that affect social norms via focusing events; and climate-induced *technological change* could set off a learning-by-doing process. Climate-society feedbacks differ from environmental and social tipping points in that they are characterized by continued interactions between the two systems. Environmental or social tipping points, by contrast occur when effects from one system lead to continued feedbacks within the other system.

There is growing empirical evidence of a large set of climate-society feedbacks that are relevant for climate policymaking. Table 1 describes various climate-society feedbacks that we identified in the academic literature organizing them by their corresponding social sector and their underlying feedback mechanism. Here we discuss these feedbacks by their underlying type.

The energy sector is a critical source of climate-society feedbacks. On the supply side, as temperatures rise, water availability changes, and storms increase from climate change, the relative efficiency of different energy sources will change. While traditional thermal power sources (coal, gas, oil, and nuclear) will become less efficient (i.e., require more emissions per unit of energy produced) due to decreased thermal efficiency and water available for cooling (Torben Mideksa & Steffen Kallbekken, 2010; van Vuuren et al., 2012; Jennifer Cronin et al., 2018), the impact on renewable energy sources is less clear and could vary regionally (Mideksa & Kallbekken, 2010; Cronin et al., 2018). Transmission of energy is also expected to be negatively affected (Mideksa & Kallbekken, 2010; Cronin et al., 2018), potentially favoring distributed generation like solar and wind. The overall impact of these changes on the carbon intensity of output is unclear as direct impacts on thermal sources and transmission will increase emission intensity, while shifts towards renewable sources of

[4] An additional group of feedbacks are climate policy feedbacks whereby the effect of a climate policy is mitigated, even backfiring, or reinforced due to interactions within the climate-economic system. We do not discuss climate policy feedbacks (Stefan Fölster & Johan Nyström, 2010) that may arise from implementing greenhouse gas policies, such as carbon taxes or technology subsidies. These are beyond the scope of this paper, as we are primarily interested in the damages from climate under Business-As-Usual and the first best policy solution.

energy sources due to their relative competitiveness will decrease emission intensity. Potentially, the impact could change over time from positive to negative as the energy sector become less reliant on centralized thermal sources.

On the demand side, higher temperatures will decrease use of energy for warming during colder months and increase energy use for cooling during warmer months as households adapt to climate change (Richard Tol, 2013; van Vuuren et al., 2012; Maximilian Auffhammer & Erin Mansur, 2014). Specifically, warmer temperatures will lead to more households investing in air conditioners and increasing their intensity of use (Auffhammer & Mansur, 2014). The net impact of this change is to increase energy demand, though the anticipated magnitude of this increase ranges widely (van Vuuren et al., 2012; Tol, 2013; Kate Larsen et al., 2017; Bas J. van Ruijven et al., 2019). Like energy supply impacts, energy demand changes will impact total GHG emissions and GHG emissions per unit of economic output.

Outside of the electricity sector, feedback effects can arise as other economic sectors and the overall economy responds to climate change. Across all sectors, economic disruptions from climate change lower economic production as rising temperatures and other climate drivers damage the economic system. As economic production declines, households adjust their savings rate downwards further compounding a decline in investment. As investment declines, economic production declines along with its corresponding industrial emissions (Nordhaus, 1994; Calvin & Bond-Lemberty, 2018). If conflict-development traps are triggered by climate change, this negative feedback effect could be further compounded (Woodward et al., 2019; van Ginkel et al., 2018; Kopp et al., 2016). In turn, investment in adaptation can mediate these damage-based feedback effects.

Change in relative productivity of climate sensitive economic sectors can also trigger feedback effects. Agriculture and forestry, along with land-use change in general, are, together, the second largest source of GHG emissions globally (IPCC, 2014) and are directly sensitive to atmospheric CO_2 concentrations (via fertilization) and exposed to climate change risks (Calvin & Bond-Lamberty, 2019; Yletyinen et al. 2019; van Vuuren et al., 2012). Increased demand for biofuels are a potential further driver of land-use changes in these sectors, while decreased livestock productivity (decreased pastureland, increased demand and changing supply of water, and increased disease pressures) and increased greenhouse gases from feed (due to decreased quality of forage quality) will impact land use and greenhouse gases directly (M. Melissa Rojas-Downing et al., 2017). Feedback effect from agriculture (including animal husbandry) and forestry could be positive or negative [5] and may shift over time as the CO_2 fertilization effect weakens (Uris Baldos et al., 2018; Annie Sneed, 2018) and temperature-related risks are realized (van Vuuren et al., 2012).[6] Land use changes in these sectors affect the release and sequestration of greenhouse gases and can be amplified by environmental tipping points, such as the loss of the Amazon forest (van Vuuren et al., 2012). There is also a close relationship between agriculture and forestry and other economic sectors (energy production, residential, and industry) via water availability (van Vuuren et al., 2012; Weyant, 2017), such that complex multi-sector feedbacks may arise.

Similarly, climate change will impact transportation, the fourth largest source of GHG emissions (IPCC, 2014). As artic sea ice melts, some shipping routes become more direct having an unclear net impact on GHG emissions (as it potentially lowers GHG intensity per unit of transport and increases total quantity of shipping provided). Increased levels of artic transport could also have local warming effects due to ozone creation (van Vuuren et al., 2012). Climate change may have a variety of negative consequences for transportation infrastructure, such as roads, railways, airports, and ports. The net effect of climate change on the relative affordability of different methods of transport (which have different emission intensities) is unclear, but even

[5] Using ESM, Thornton et al. (2017) finds a negative feedback whereby increased crop yields from climate change (in RCP 4.5 and RCP 8.5) result in decreased agricultural land, increased forests, and increased competitiveness of biofuels. Similarly, Calvin et al. (2019) finds evidence that this feedback reduces CO_2 by approximately five parts per million weight. Other studies, like Bojana Bajželj and Keith Richards (2014), find a positive feedback from negative climate impacts on agriculture yields. It is unclear if these modeling exercises are consistent with the most up-to-date meta-analysis of agricultural yield impacts (Frances Moore et al., 2017).

[6] Regional temperatures are influenced by environmental tipping points (Kopp et al., 2016), which can greatly impact agriculture regionally.

relatively minor shifts in transportation choices could have significant aggregate effects on emissions (van Vuuren et al., 2012).

Various adaptation measures may lead to positive feedbacks, especially through increased energy usage. Increased electricity demand for air conditioning is one example, but other forms of technological adaptation will also increase electricity demand. The construction and use of desalination plants to respond to declining water availability requires energy (van Vuuren et al., 2012). Additionally, extensive coastal protection (Tol, 2007; Tol, 2013) could lead to significant GHG emissions depending on the construction methods and materials. Some climate-induced migration may be from low emission per capita countries to high emission per capita countries—leading to a net increase in emissions—although most of climate migration will likely be within country and region (Richard Black et al., 2011; Francois Gemenne, 2011).

Another source of climate-society feedbacks is via social and political institutions. As noted by Kopp et al. (2016), climate impacts and tipping points may act as focusing events that led to political pressure for more aggressive carbon reduction policies. Andrew Jarvis et al. (2012) models temperature directly impacting emissions (i.e., carbon intensity of energy), as society adopts less carbon intensive sources of energy to prevent future climate change. Beckage et al. (2018) models the effect of focusing events on climate policy, finding that these effects increase the variability of potential temperature change, but eliminate extreme impact scenarios due to negative feedbacks.

Although it is possible that focusing events will lead to greater investment in mitigation and adaptation, climate change may also disrupt the ability or willingness of political institutions to adopt climate policies that have longer-term payoffs but short-term costs. Climate change induced shocks to economic growth or civil unrest could lead policymakers to devote more of their limited attention to more immediate concerns. Significant evidence points to climate change increasing the risk of civil and political conflict within countries (Solomon Hsiang et al., 2011; Melissa Dell et al., 2014; Marshall Burke et al., 2015; Tamma Carleton & Hsiang, 2016; Kopp et al., 2016). Using global treaty data, Howard and Livermore (2019) demonstrate that increased civil conflict decreases participation in international environmental cooperation efforts. Climate-driven political instability and social conflict could further undermine climate action if they erode democracy, particularly if they also increase corruption, reduce public participation and/or shift governments to the right (Tiago Neves Sequeira & Marcelo Serra Santos, 2018; Haiqing Hu et al., 2021). Joshua Conrad Jackson et al. (2019) finds strong evidence that climate change and other ecological pressures increase cultural prejudice and support for right-wing political groups and policies, which may be less likely to support strong climate policies.[7]

Beyond effects on political institutions, climate change may induce a wide range of behavioral changes that could feed back into the climate system. Focusing events may increase consumer demand for energy efficiency and mitigation technologies.[8] If these industries experience learning by doing, this could set off a positive feedback with the economic system that decreases costs. Intertemporal preferences may shift due to catastrophic climate risks: as these risks increase, the pure rate of time preference, which is affected by existential risks (Michael Stern, 2007), should also increase (Wilfred Beckerman & Cameron Hepburn, 2007; Yacov Tsur & Amos Zemel, 2009). This would lead to a decreasing willingness to trade short term costs for long term benefits. Societal shifts in time preferences may be dynamic, non-linear, and unstable depending on the factors

[7] Climate action may also create a negative feedback effect via the political system if climate-action creates political support for right-leaning parties that favor industry over environmental preservation. For example, in the United States, loss of coal jobs has increased support for the Republican party in the impacted regions and regions nearby (Florian Egli et al., 2020).

[8] Psychology has identified multiple barriers to climate inaction, including "limited cognition about the problem, ideological worldviews that tend to preclude pro-environmental attitudes and behavior, comparisons with key other people, sunk costs and behavioral momentum, discredence toward experts and authorities, perceived risks of change, and positive but inadequate behavior change." Behavioral changes may result if these psychological barriers are overcome, as in the case of a focusing event. Then, just as these psychological barriers currently act to limit climate action, they can then act to reinforce climate action (Robert Gifford, 2011). For example, targeted messaging (potentially around a focusing event) combined with changing social norms may lead to significant change in action (Gifford, 2011), as recently noted in the reduction in Swedish air traffic due to "flight shaming" (BBC, 2020).

that influence such shifts (Donges et al., 2018). Climate change may induce behavioral changes directly by impacting the relative value of household activities with different carbon footprints. For example, Nordhaus and Joseph Boyer (2000) find that climate amenities may improve for some level of warming leading to increased recreational opportunities, and Nick Obradovich and Iyad Rahwan (2019) find statistical evidence that U.S. households drive more in a warmer climate.

The prior discussion of climate-society feedbacks is exploratory rather than comprehensive. Significant work is necessary to identify and establish the magnitude of these and other feedback effects. In undertaking this work, there are several characteristics of climate-society feedbacks that should guide analysis. These include the importance of scale—some climate-society feedbacks occur at the global scale, but may be locally differentiated due to environmental conditions and various social, cultural, and economic factors. Like environmental and social tipping points, climate-society feedbacks also involve deep uncertainty, lags, hysteresis, non-linear dynamics, and the potential for regime shifts. As environmental, social, and climate-society systems dynamically interact over time, unexpected emergent proprieties can arise (Boumans et al., 2015), especially as global connections increase over time.

2.2 Modeling in IAMs

The social cost of carbon (SCC) used in cost-benefit analyses of major federal regulation in the United States relies on the three most cited reduced-form integrated assessment models (see Supplementary Material for a taxonomy of integrated assessment models). This subset of reduced form IAMs, known as social-cost IAMs (SC-IAMs) (NAS, 2017), are the Dynamic Integrated model of Climate and the Economy (DICE); the Framework for Uncertainty, Negotiation and Distribution (FUND) model; and the Policy Analysis of the Greenhouse Effect (PAGE) model. Other reduced-form IAMs capable of estimating the SCC, include hybrid IAMs like World Induced Technical Change Hybrid Model (WITCH) and Model for Evaluating Regional and Global Effects of GHG Reduction Policies (MERGE) (Valentina Bosetti et al., 2006; Alan Manne & Richard Richels, 2005)[9] that combine a top-down macroeconomic growth model and a bottom-up technology model as well as a small subset of analytic IAMs that make simplifying assumptions to find a closed-form solutions for the social cost of carbon. (e.g., Inge Van den Bijgaart et al., 2016).[10] However, we focus our attention on the three SC-IAMs due to their prominence in research and U.S. policy (Bosetti, 2021), as their aggregate structures are particularly designed to calculate the social cost of carbon and the socially optimal carbon tax (NAS, 2017). Additionally, the hybrid nature of these other IAMs adds additional (potentially unhelpful) complexity and analytic IAMs are not-well suited for including feedback effects due to tractability requirements (IWG, 2010; NAS, 2017). Despite our focus on and preference for SC-IAMs in the climate policy context, we will discuss potential substitute and complimentary IAM approaches; see our taxonomy of IAMs in our Supplementary Material section.

SC-IAMs capture environmental tipping points to a limited extent but essentially exclude most social and climate-society feedback effects. Specifically, SC-IAMs capture environmental feedback effects to the extent that they are explicitly represented in an underlying climate model or explicitly represented as a feedback effect

[9] WITCH and MERGE are hybrids between a reduced-form IAM, like a SC-IAM, and a detailed-structure IAM (discussed later) leading some to classify the models as the former (Gustav Engström & Johan Gars, 2015) and others to classify it as the latter (IPCC, 2018; Allen Fawcett et al., 2009). Consequently, modelers use WITCH and MERGE to develop socioeconomic emission scenarios along with other detailed-structure IAMs, while also being capable of estimating the SCC when analysis exercise that the option to include a climate-damage function (Geoffrey Blanford et al., 2009; IWG, 2010; Keywan Riahi et al., 2017; Simon Evans & Zeke Hausfather, 2018; Kenneth Gillingham et al., 2018).

[10] In general, analytic IAMs are a subset of stochastic dynamic IAMs (discussed later). Analytic IAMs are simplified models that allow for closed-form solutions to the optimal carbon tax and, in some cases, the social cost of carbon. These models require stylized and highly simplifying (and potentially incorrect) assumptions to maintain tractability (OECD, 2018; Lemoine, 2021). Since their development in Golosov et al. (2014), analytic IAMs increasingly relax these assumptions over time to improve their approximation of numerical estimates (Lemoine & Rudik, 2017; Traeger, 2021). However, even then their primary advantage is their ability to aid policymaker understanding via their relative simplicity (J. Doyne Farmer et al., 2015; OECD, 2018), and yet analytic IAMs have not been embraced by policymakers. Additionally, their strong simplifying assumptions make them less ideal for modeling feedback effects.

within the set of equations that represent its climate-economy system. For example, climate-feedback effects due to water vapor, clouds, snow, and ice (NAS, 2016) transform an approximately 1°C of expected warming from a doubling of CO_2 concentrations without feedbacks to approximately a long-run equilibrium amount of expected warming of 3.1°C (IWG, 2010; Nordhaus, 2017).[11] However, some known feedback effects are not incorporated into the relevant climate models (NAS, 2016), although steps have been taken in newer climate models to integrate environmental feedback effects, like the melting of permafrost, into their simulations (Kopp et al., 2016; Dmitry Yumashev et al., 2019). Even so, many climate tipping points are still missing from coupled climate models, and thus, in many cases, from SC-IAMs and IAMs more generally (Kopp et al., 2016).

Each of the SC-IAMs explicitly model some carbon cycle feedback effects that are ignored by the main climate models. However, the SC-IAM differ in their representation of the climate and the feedbacks that are explicitly captured (NAS, 2016). DICE-2016R (Nordhaus, 2017) captures the negative feedback effect that oceans have on surface temperatures by being a carbon sink (NAS, 2016), while FUND explicitly ignores this effect (Stephanie Waldhoff et al., 2014). On the other hand, PAGE09 abstractly models a positive climate cycle feedback effect via a feedback response time parameter (Chris Hope, 2013; NAS, 2016) and PAGE-ICE (Yumashev et al., 2019) also explicitly models permafrost carbon and non-linear surface albedo feedbacks,[12] while FUND explicitly models a positive feedback effect resulting from a warming of the terrestrial biosphere and the resulting dieback of vegetation like tropical forests (Waldhoff et al., 2014; NAS, 2016). However, DICE does not model these positive feedback effect. Thus, each SC-IAM differs in the carbon cycle feedback effects explicitly modeled in its climate system.

In the base versions of the models used by policymakers, SC-IAM developers have also traditionally implicitly or explicitly captured other environmental feedback effects that underly tipping points that directly impact human welfare. Again, there have been differing approaches. In its base version, FUND does not account for any tipping points except for the feedbacks discussed above. However, David Anthoff and Richard Tol (2014) argue that they capture catastrophic outcomes by running a Monte Carlo simulation with hundreds of uncertain parameters. Earlier versions of DICE, which relied on an enumerative damage function calibration (Nordhaus & Boyer, 2000), included a measurement of certainty equivalent damages of catastrophic events based on a survey of experts (Nordhaus, 1994b; Nordhaus & Boyer, 2000)—this implicitly captured the damage of tipping points to the extent that experts considered them in their survey responses. However, for DICE-2013R and DICE-2016R2, Nordhaus moved to a meta-analysis strategy for calibrating the DICE damage function that essentially omits catastrophic impacts (Howard, 2014).[13] In PAGE09 and PAGE-ICE, Hope explicitly models an abstract tipping point in the default version of his model, while its value is adjusted downwards in PAGE-ICE relative to PAGE09 to account for the explicit modeling of Arctic feedbacks in PAGE-ICE. Specifically, in PAGE, Hope explicitly models a discrete event that has a probability of occurring in each time period when the realized temperature is above a specified temperature threshold (with central values of 3°C and 1.5°C in PAGE09 and PAGE-ICE, respectively), and this probability is increasing in temperature. Despite capturing some set of the environmental and social tipping points discussed by Kopp et al. (2016), it is unclear the extent to which these methods capture the underlying feedback effects (Yumashev

[11] As the impacts of these feedbacks on the long-run amount of warming from a doubling of carbon dioxide are highly uncertain, the equilibrium climate sensitivity parameter that captures this impact in climate-economy models is often represented by a fat-tailed distribution (IWG, 2010).

[12] Albedo is already included in the equilibrium climate sensitivity parameter in other SC-IAMs using a constant, instead of non-linear, value (Yumashev et al., 2019).

[13] In Nordhaus' meta-analyses (Nordhaus & Sztorc, 2013; Nordhaus & Andrew Moffatt, 2017), most of the underlying sources do not account for environmental tipping points or catastrophic damages. Thus, the model essentially omits tipping damages. To account for omitted damages, including non-market and catastrophic impacts, Nordhaus adjusts his meta-analysis damage function upwards by 25%. As the catastrophic component in earlier versions of DICE would imply an adjustment for the DICE-2013 estimates of between 62% and 91%, Howard (2014) argues that the latest DICE models essentially omit catastrophic impacts.

et al., 2019). PAGE-ICE also represents potential sea-level rise using a fat tailed distribution to capture the potential collapse of the Greenland and West Antarctic icesheets (Yumashev et al., 2019).[14]

Alternatively, stochastic dynamic IAMs develop a more sophisticated representation of tipping points, which include the possibility of multiple correlated tipping points. Yongyang Cai et al. (2016) calibrates a stochastic dynamic version of DICE (DSICE) to an expert survey (Elmar Kriegler et al., 2009) to capture five environmental tipping points discussed above: the collapse of the AMOC, the dieback of the Amazon, the melting of the West Antarctic Ice Sheet, the melting of the Greenland ice sheet, and the increased frequency of El Niño-Southern Oscillation events. They find an 800% increase in the optimal carbon tax with their inclusion. Alternatively, in another stochastic dynamic version of DICE, Derek Lemoine and Christian Traeger (2016) model three, connected abstract tipping points that reflect: the possibility of runaway climate change (i.e., higher equilibrium climate sensitivity parameter) from melting of permafrost and methane hydrates and melting of ice sheets; longer residency time for GHG to remain in the atmosphere from weaker carbon sinks (oceans, soil, and biomass); and higher than expected damages from crossing thresholds such as weakening of the AMOC, collapse of ice sheets, and loss of habitat from diebacks. They find a 100% increase in the optimal carbon tax with their inclusion. Even so, SC-IAMs remain more policy-relevant than stochastic dynamic IAMs, partially due to their transparency via simplicity (Benjamin Crost & Traeger, 2013) and their ability to provide a marginal damage estimate on a non-optimal emission trajectory (i.e., the social cost of carbon). With respect to our goal of more fully representing climate-society feedbacks, SC IAMs are also more relevant as stochastic-dynamic models must simplify the state space due to the curse of dimensionality, though numerical methods are improving to overcome this issue (Traeger, 2014; Lemoine & Ivan Rudik, 2017).

Another solution is to incorporate feedback effects into SC-IAMs in some scientific detail using empirically based equations of the underlying process and its impacts (Kopp et al., 2016).[15] Kopp et al. (2016) summarizes various examples of tipping points being included in SC-IAMs, including permafrost, the AMOC collapse, and ice sheet collapse.[16] Thus far, these additions are usually done one at a time (i.e., not modeled simultaneously) and are not included in the base version of the SC-IAMs. As such, these model runs fail to capture the correlation and interaction of tipping points and are excluded from policy analysis (which typically rely exclusively on the base version of the models). An exception is the inclusion of the permafrost carbon and surface albedo feedbacks in PAGE-ICE in a reduced-form manner using emulators (Yumashev et al., 2019).

Social feedback effects are not modeled in the leading SC-IAMs. Few of the models have the capacity to explicitly model the social feedback effects and their corresponding tipping points (some of which were discussed in Kopp et al. (2016)). None of the models explicitly model political behavior, conflict, or learning, and only FUND models migration behavior, but without tipping points. One reason that social feedback effects are difficult to model in SC-IAMs is that simplifying assumptions concerning rationality and perfect information set aside effects from learning by doing and focusing events (Donges et al., 2017; Beckage et al., 2018). SC-IAMs also do not model the interactions between sectors of the economy, thereby excluding potential inter-sector feedback effects. SC-IAMs could capture some social feedback effects implicitly in model parameters, for example by accounting for conflict risks in the overall net-damage function, but SC-IAMs do not currently do so (Howard, 2014).

Three alternative IAMs do partially address social feedback effects. Partially enabled by their hybrid structures, WITCH and MERGE account for endogenous technical change and learning by doing (Manne & Richels, 2005; Bosetti et al., 2006; Adriana Marcucci & Hal Turton, 2012). As such, they should capture the positive feedback effects that arises between mitigation and mitigation costs. Alternatively, following the

[14] To avoid double counting, the abstract tipping point in PAGE-ICE no longer capture feedback effects and tipping points represented elsewhere in the model: permafrost, snow, and sea ice loss in the Arctic and collapse of ice sheets. Therefore, the magnitude of the loss from the triggering of the tipping point in PAGE-ICE is less than PAGE09 (Yumashev et al., 2019).

[15] If this feedback effect is not represented by the sophisticated global climate model to which the SC-IAM is calibrated, it is critical to turn off the additional feedback effect code during calibration (NAS, 2016).

[16] Since then, additional studies have been published including Nordhaus (2018) on the collapse of the Greenland ice sheet.

development of SC-IAMs, several modelers built computable general equilibrium (CGE) integrated assessment models; these include the Environmental Impact and Sustainability Applied General Equilibrium Model (ENVISAGE), the Intertemporal Computable Equilibrium System (ICES) model, and the ENV-Linkages model (Roberto Roson & Dominique van der Mensbrugghe, 2012; Francesco Bosello et al., 2012; Rob Dellink et al., 2019). These models formally represent feedbacks between the climate and the economy as well as inter-sector relationships within the economy (Dellink et al., 2019). In doing so, they capture potential feedbacks in the climate-economy system as sub-systems move towards general equilibrium.

More recently, ecological macroeconomists have applied agent-based IAMs (AB-IAMs) to the climate-economy system. AB-IAMs attempt to model behavior at the microeconomic scale and then predict macroeconomic phenomena; this approach stands in contrast to SC-IAMs, which contain reduced-form representations of macroeconomic behavior. The AB-IAMS are based on models of heterogenous individual actors (individual households and firms) and their decisions within a hierarchical structure (neighborhoods and industrial sectors) (An et al., 2012, 2014; Francesco Lamperti et al., 2019). AB-IAMs capture social interactions and feedbacks that are explicitly modeled via decision rules and those that emerge implicitly (Lamperti et al., 2019). AB-IAMs are unique in their ability to represent feedbacks that arise implicitly from connections between the micro and macro phenomena. AB-IAMs are at an early stage of development (Brian Miller & Jeffrey Morisette, 2014; Lamperti et al., 2019) and already explicitly represent the adoption of green technology (Lamperti et al., 2019), but they are theoretically capable of explicitly modeling social tipping points like conflict, migration, and politics.

Like social tipping points, climate-society feedback effects are mostly excluded from SC-IAMs. One exception is in DICE and other IAMs that model GDP endogenously and capture the impact of the climate system on the economic system using damage function(s). Unlike FUND and PAGE, DICE does not assume an exogenous GDP path. Because GDP predictions are based on a continually updated investment function, DICE captures the negative impact that climate change has on future GHG emissions, through reductions in future capital investments. Additionally, AD-DICE, an extension of DICE that explicitly model adaptation and its costs, capture an opposing positive feedback that arises as adaptation reduces the negative impact of climate change on investment via damages, which in turn leads to more GDP and emissions by delaying mitigation and the transition to zero and negative emission technologies (Kelly De Bruin et al., 2009). All other climate-society feedbacks (detailed in Table 1) are excluded.[17]

Hybrid, CGE models, and AB-IAMs only fractionally improve on this limited representation. Like DICE, these IAMs capture the negative production feedback effects when GDP is endogenously determined within the models' structure. Additionally, CGE and hybrid IAMs (WITCH and AD-MERGE) also capture the adaptation feedback effect represented in AD-DICE by also explicitly modeling adaptation and its costs (Bosello et al., 2010; Oliver Bahn et al., 2019).[18] WITCH also captures feedbacks that arise from endogenous land use change, though not via climate-driven yield changes, using an emulator (Manne & Richels, 2005; Johannes Emmerling et al., 2016). Finally, by more explicitly modeling the links between climate damages (and adaptation), economic actors/sectors, and the diffusion of impacts within the joint climate-economy system, these IAMs capture emergent climate-society feedbacks. Even so, without explicit modeling, these alternative IAMs still fail to model many climate-society feedbacks listed in Table 1. Moreover, of these three alternative IAMs, only hybrid IAMs are currently used to estimate the SCC.

3. Social Ecological System and Related Research: Lessons Learned

The climate-economy system is characterized by an important set of feedbacks that are not well represented in the IAMs, including SC-IAMs, that are used by governments around the world to inform climate policy.

[17] Despite PAGE's traditional non-optimal structure, such that GDP is exogenous, its developers are updating PAGE-ICE to allow for climate damages to modify the GDP pathways via growth impacts (i.e., damage persistence). As of now, the current version of PAGE-ICE does not appear to adjust the emissions pathway along with the GDP pathway. Consequently, PAGE-ICE does not capture the GDP feedback in DICE (J.S. Kikstra, 2021).

[18] CGE-IAMs partially model adaptation by capturing production adjustments via substation between inputs and trade adjustments in response to climate impacts (Dellink et al., 2019).

Improving the modeling of climate-society feedbacks, especially, should be a priority for the climate research community. Although this endeavor raises several challenges, researchers can draw from experience in several interdisciplinary literatures that address socio-ecological system (SES) feedbacks. These include a strand of literature that arises out of Ostrom's work on common goods (Claudia Binder et al., 2013), the CHANS literature, which focuses on coupled human-landscape systems, and literatures on integrated human-earth system modeling and ecological macroeconomics, both of which recognize the importance of understanding links between the social and ecological systems (Lukas Hardt & Daniel O'Neill, 2017; Lamperti et al., 2018). In this section, we review these literatures to extract useful lessons for the project of better incorporating feedbacks into climate-economy models.

3.1 Lesson 1: There are a variety of tools available for modeling climate-society systems

Despite similar underlying goals, the different contexts for these subfields result in different strategies to integrate social-ecological system (SES) feedbacks into their modeling strategies. In attempting to address traditional model shortcomings, the literatures developed multiple frameworks (i.e., ways of viewing SES) upon which climate-economics can draw to analyze the climate-society system (Binder et al., 2013): SES framework (SESF), Human Environmental Systems (HES) framework, and the Management and Transitions Framework (MTF) (Binder et al., 2013). Critically, each of these frameworks provide guidance on how to consider and model two-way feedbacks (Binder et al., 2013) in addition to providing a set of common assumptions, concepts, and practices for conceptualizing SES. While not providing a standardized approach, frameworks provide guidance on the selection of the appropriating modeling tool (Binder et al., 2013). Using these frameworks, these disciplines have refined their modeling approaches.

From these multi-disciplinary approaches, several modeling tools are particularly relevant in the climate-economy context (Schlüter et al., 2012). For our context of macroeconomic climate-economy models, there are three key modeling approaches in the literature: integrate detailed-structure IAMs and earth-system models; modify (neoclassical-based) SC-IAMs or hybrid IAMs; and develop agent-based IAMs. As is clear from the titles, each of these model alternatives are classifiable as integrated assessment models as they integrated climate and economic models in different ways. We discuss each of these IAMs in turn.

In earth system modeling, there is widespread acknowledgement of human influence on earth systems and the existence of interactions and feedbacks. However, there is often limited knowledge about specific interactions and feedbacks (van Vuuren et al., 2012). Within this field, there has been a growing call to link detailed-structure IAMs, also known as detailed process IAMs and less commonly referred to as cost-effectiveness and policy-evaluation IAMs, with earth system models to understand how these interactions impact emission scenarios (van Vuuren et al., 2012).[19] Specifically, these models link a detailed-structure IAM – an IAM with detailed representations of climate systems, climate impacts and adaptation, and energy and technology (including costs of mitigation and adaptation) – with a sophisticated climate model that includes related earth systems, including land cover, water-cycle, organic carbon, nitrogen, and phosphorus cycles, and others in addition to atmospheric chemistry and climate (van Vuuren et al., 2012). Unlike SC-IAMs and hybrid IAMs, detailed-structure IAMs do not have climate damage functions.[20] These linkages can take on different levels of formality based on: the evidence of SES existence, its process, and its strength; the required level of model sophistication necessary to capture the relevant interactions; and the necessary scale of the various systems to accurately depict the key features of the interaction (van Vuuren et al., 2012). This has become the primary tool for human-earth system modeling to develop climate scenarios and measure climate impacts (e.g., agricultural, forestry, hydrological, land use, etc.) (Calvin & Bond-Lamberty, 2018; United States Department of Energy, 2016).

SC-IAMs represent an integrated human-earth system model with linkages between the two systems (Calvin & Bond-Lamberty, 2018). Specifically, SC-IAMs integrate a simple climate model into a neoclassical economic

[19] Some commonly applied detailed-structure IAMs include: AIM, IMAGE, GCAM, MESSAGE, and REMIND (IWG, 2010; Weyant, 2017; IPCC, 2018).

[20] Other than hybrid models like WITCH and MERGE, discussed earlier, detailed-structure IAMs also do not have damage functions. Hence, the alternative terminology of policy-evaluation and cost-effectiveness IAMs.

growth model with a damage function as the primary link (Nordhaus & Boyer, 2000). Thus, the distinction between the first and second of these modeling approaches is predominately driven by the differences in policy-optimization versus policy-evaluation, the sophistication of the climate model, and the level of formality in integration (See Section 3.4). No publication to our knowledge discusses how to include SES within SC-IAMs; accordingly, we propose a methodology in Section 4.

Finally, agent-based IAMs represent a significant departure from the traditional IAMs discussed above. In general, agent-based models are common in the CHANS research as they can represent the structures and processes of CHANs (An et al., 2014). Specifically, agent-based models develop bottom-up modeling of macroeconomic behavior where heterogenous individual agents are tracked with various state variables, as they interact and make decisions within hierarchical social structures (An et al., 2012; An et al., 2014; Schlüter et al., 2015). As discussed above, this allows agent-based models to explicitly capture social interactions and feedbacks at various hierarchical levels, including networks, and allow for interactions to implicitly arise. Due to their complexity, the modeler must make many relevant decisions in developing their final specification: key social and environmental actors, the relevant social organizations and the actors' position within these hierarchal structures, their decision rules, their linkages (e.g., networks), and the appropriate spatial and temporal resolution (given these linkages) (An et al., 2012; An et al., 2014; Miller & Morisette, 2014). Given this wide range of specifications, agent-based models can vary in their level of detail from basic to extremely complex.

AB-IAMs essentially introduce agent-based modeling into ecological macroeconomics models; Dystopian Schumpeter meeting Keynes (DSK) (Lamperti et al., 2017) is the first agent-based IAM. To move the economy toward sustainability (and sustainable economic policy), ecological macroeconomics aims to represent the dependency of the economic system on the environment and the interactions between the two (Hardt & O'Neill, 2017). Additionally, ecological macroeconomics breaks with the application of neoclassical economics in IAMs in several ways, including: by introducing alternative growth models (e.g., a Keynes growth model in Lamperti et al. (2018) or post-Keynesian growth models discussed in Hardt and O'Neill (2017)) with often fuller and more sophisticated representations of the economy;[21] replacing rational behavior and perfect information assumptions with alternative theories of human decision making (Hardt & O'Neill, 2017; Lamperti et al., 2018); including a financial sector with credit constraints; disaggregating production and consumption, including modeling the connection of industries; including multiple business models; and the modeling of employment, working time, and economic inequality. This increase in complexity is challenging to model at the aggregate level and agent-based models (including AB-IAMs) are one potential way forward (Hardt & O'Neill, 2017). By replacing the representative agent (and his/her aggregate social welfare function) in SC-IAMs with multiple individual agents, AB-IAMs can drop the "ad hoc" social welfare function and represent inequality (Lamperti et al., 2019). Finally, by introducing agent-based modeling into more sophisticated IAM structures, AB-IAMs can more fully study the properties of the joint systems with a richer representation of real-world complexity (heterogeneity, interactions, feedbacks, hierarchical structures, and networks) that enables study of emergent properties, including sustainability, in the climate-economy system (Miller & Morisette, 2014; An, 2012). This advantage of potential realism comes with the usual drawbacks of complexity in terms of tractability, ease of understanding, data intensiveness, and difficulty verifying results. These differences can result in significantly different modeling outcomes than SC-IAMs, as evidenced by six-fold lower cumulative GDP by the end of century between DSK and DICE despite similar damage functions, leading Lamperti et al. (2019) to assert that more realistic assumptions about the economy increase climate impacts.

Each of these models are not mutually exclusive. It is possible to integrate more sophisticated climate models into SC-IAMs, as suggested by National Academy of Sciences (2017). Similarly, it is possible to integrate agent-based models into detailed-structure IAMs (Miller & Morisette, 2014). Alternatively, other SES modeling tools can be useful when integrated into the various types of IAMs.[22] For example, when spatial and landcover feedback effects are particularly relevant, spatially explicit landscape models (e.g., MIMES, InVEST, ARIES,

[21] Feedbacks are rarely captured in ecological-macroeconomic models (Hardt & O'Neill, 2017)

[22] Several of these modeling tools are less relevant for the purposes of climate-economy models, including bioeconomic models traditionally used in renewable resource management problems (e.g., fisheries, rangeland, and wildlife) (Schlüter et al., 2012; Schlüter et al., 2015).

and Tradeoff optimization) allow for the representation of non-linear connections between ecosystem services production and economic activity at various spatial scales (local, regional, and global) (Boumans et al., 2015). In the context of climate-economy feedbacks, landcover models are important to include when capturing positive and negative feedback effects arising from the biosphere (such as forest diebacks) or human-landscape (such as farming and forestry) changes (Boumans et al., 2015). Similarly, spatial models like species distribution models can be integrated as well (Miller & Morisette, 2014).

The frameworks that aided in the development of these new modeling tools can also aid in the selection of the appropriate model for considering SES feedbacks in a particular context (Bentley et al., 2013). In our case, the goal of including SES feedbacks in a policy relevant IAM to estimate policy statistics, like the social cost of carbon, leads us towards SC-IAMs. In particular, many policymakers have gained familiarity with SC-IAMs in the process of developing and using the social cost of carbon (IWG, 2010).

3.2 Lesson 2: Modelers should focus on representing climate-society feedbacks critical to human welfare

Models should capture large feedbacks that matter on a human timescale. Economics is an anthropocentric social science concerned with maximizing human welfare. Feedback effects that only slightly impact human systems are not worth the additional modeling effort or additional complexity, as they will have little impact on climate policy (see Section 3.5). Similarly, just as Kopp et al. (2016) differentiates between abrupt tipping points and tipping elements on the environmental side of climate modeling, modelers should similarly focus their attention on social and climate-society feedbacks that matter on a human timescale. Due to discounting, feedback effects that operate on century-long or millennial timescales will barely factor into current policy decisions. Traditionally, the relevant timescale has been approximately 300 years (IWG, 2010), though recent work by Lemoine (2021) extends this relevant range out to 600 years under uncertainty (Lemoine, 2021).

Future research is necessary to determine the magnitude of these climate-society feedbacks. While Kopp et al. (2016) is able to classify many environmental feedbacks as causing tipping points or tipping elements, climate-society systems research is only in its initial stages. Currently, it is often difficult to determine the directional sign of these impacts or determine whether they are significant or relevant in a human timescale. To explicitly include these climate-society systems into models, better estimation of their magnitude and lag time is critical.

3.3 Lesson 3: Focus on key nodes in the system (i.e., events), rather than identifying all possible connections

Within a modeling system, there are critical nodes (actors, sectors, and events) and connections between these nodes. For example, displaced households and the possibility of climate-induced mass migration could be critical nodes, actors, and events, respectively; see Table 1. Alternatively, key connections to capture in the phenomenon of climate-induced migration include: the connections between climate factors (such as droughts and sea level rise) and migration; social networks that connect sending and receiving nations in the migration system; the impacts of regional populations and emission intensity; and the impact of migration on political views. Likewise, we can think of increased model complexity as arising from the expansions of the nodes within the economic system to include more actors/sectors and events and/or an increase in connections within the system. For example, AB-IAMs and CGE IAMs increase the number of connections in the joint system by increasing the nodes, while globalization is a phenomenon that increases the number of connections in the system even while holding the number of nodes constant (Calvin & Bond-Lemberty, 2018). In a stochastic model, it is critical to represent nodes and connections because they can enable the realization of catastrophic, compound events (Claudio Cioffi-Revilla, 2016). In our case of climate-induced migration, a compound event could be a shift of the global political system towards climate denial that occurs as a consequence of higher-than-expected sea-level rise and other climate realizations, large-scale migration from developing to developed nations, and crossing of critical political thresholds. A major reason for modeling SES feedbacks is to capture the possibility of these catastrophic compound events and the real possibility of irreversible large-scale losses than can arise due to the web of connections within a joint system.

A critical finding in the SES literature is that the probability of compound events is more strongly influenced by the probability of a negative event (i.e., nodes) than by connections (Cioffi-Revilla, 2016). This

simple result has several major implications for SES modeling and policy. In terms of (stochastic) modeling, this result implies that modelers should focus on representing the critical nodes (i.e., actors, social systems, sectors, and events) rather than connections (Cioffi-Revilla, 2016). In our example above, migration represents a critical node within the system. Additionally, while modelers should focus on capturing all critical nodes in the scale of the model, modelers must also ask whether the scale of the model (time, space, hierarchy, and micro representation) is sufficient to capture key nodes explicitly. For example, if capturing the possibility of mass migration is critical, it may be necessary to consider whether models need to capture heterogenous, individual agents or merely a simple representation of migration, as in FUND. If the model is at too aggregate of a scale, modelers should ensure that these key events are captured implicitly. In our climate-induced migration example, SC-IAMs, like DICE, could include the cost of migration in the damage function calibrated to existing study estimates. From this perspective, capturing all critical nodes is more important than representing all connections when choosing the scale of the model. Modeling uncertainty is also essential for low probability, compound events.

In terms of policy, this finding implies that to improve SES resilience, policy should focus on reducing the probability of negative individual events critical to the occurrence of catastrophic, compound events instead of focusing primarily on reducing connections between nodes. Specifically, policymakers could modify laws and institutions to reduce the probability of high impact events. In our example of mass migration, policymakers should not aim to break apart migration networks, but instead should reduce the probability of the critical steps leading to mass-scale migration. This could include adopting a variety of policies: mitigation policies that reduce the probability of large temperature increases; building seawalls in vulnerable areas with large populations to reduce the probability of mass displacement events; changing laws and creating institutions to resettle populations regionally in climate insensitive locations to reduce the probability of sudden mass international migration, etc.

It may be difficult for researchers and policymakers to identify the specific key nodes in the climate-economy system given its complexity. The empirical work described in Table 1 highlights relevant climate-society feedbacks, which should help in identifying critical nodes. In particular, identifying strong feedbacks and their overlapping nodes can highlight key modeling needs. The SES framework, which is essentially "an extensive multitier hierarchy of variables that have proven to be relevant" in SES, can also aid in selecting the nodes and variables that can best improve the description of an SES system and its dynamics (Binder et al., 2013).[23] Alternatively, agent-based modeling can also help with identifying key nodes by highlighting connections via emergent properties (An et al., 2014; Boumans et al., 2015; Lamperti et al., 2019). The first two techniques can be applied earlier in the development of climate-economy models, while the input requirements of AB-IAMs make them more appropriate later in the research process for further refinement.

3.4 Lesson 4: The most sophisticated method of coupling models is not always ideal

In modeling SES systems, modelers often face the decision on how to connect the social and environmental system models. In the case of IAMs (social-cost, detailed-structure, and agent-based), modelers must select the level of complexity of each system. There exists a variety of tradeoffs when determining the appropriate level of coupling between the social and environmental models. Given the discussion in Section 3.3, it is clear that selecting the most sophisticated economic and climate models, which requires a full coupling of sophisticated models, is not always the best option (van Vuuren et al., 2012).

There are three options when coupling social and environmental system models; the choice between these options should be driven by the strength of the connection between the systems and the uncertainty underlying these connections (van Vuuren et al., 2012). The most informal of these options is to exchange information between the two models. For example, a modeler can calibrate an exogenous temperature path within an economic model using a climate model. This method is appropriate when feedbacks are weak or non-existent, or when scientific knowledge is insufficient. In this case, the benefit of extensive modeling of interactions is outweighed by various costs (the difficulty of linking the models, development of new modeling techniques,

[23] Schlüter et al. (2012) states that the SES framework "makes explicit the normative and theoretical choices for the representation of major variables and interactions and the empirical evidence used in model development."

and increased complexity). Essentially, the insignificant and unclear impact on the final model outcome does not justify the additional modeling time and decreased transparency of the modeling results (van Vuuren et al., 2012).

Alternatively, modelers can improve the representation of one system in the model of the other system. In the climate-economy context, this can be done by either increasing the detail of the climate system within IAMs or increasing the detail of social systems in a climate model. This approach is ideal when the representation of only one system is necessary in detail and the feedbacks, while significant in their impact on model outcome, are not well enough understood to represent their underlying processes accurately.

Finally, modelers can fully integrate an earth systems model and an IAM. This approach is worth the considerable challenge when interactions are significant and well understood, such that simpler representations of the underlying systems are insufficient to capture the necessary detail. This can be particularly important when interactions may vary significantly over time and space (van Vuuren et al., 2012).

We use this linkage taxonomy to classify various modeling options. Of the three modeling options discussed above, those models that require optimization should not include too much detail of the climate-economy system due to tractability. Thus, only modelers considering the integration of detailed-structure IAMs and earth system models can truly consider all three options. Alternatively, SC-IAMs and AB-IAMs integrate a simplified climate model into a (neoclassical or heterodoxic) growth model; this is the second option. However, relative to traditional SC-IAMs and reduced-form IAMs more generally, AB-IAMs essentially focus on improving the representation of economic systems to represent interactions more fully within the SES. In Section 4, we propose a methodology of improving the representation of linkages within an SC-IAM without modifying the representation of either system significantly. Given the *potential* significance of SES feedback effects and the level of uncertainty underlying many of their processes, this middle ground is a sensible approach forward at the current moment.

3.5 Lesson 5: Tradeoff between complexity and simplicity

In modeling SES, modelers must balance complexity and inference (Calvin & Bond-Lemberty, 2018). On one hand, IAMs need to model complexity if they aim to completely represent all feedback effects (Calvin & Bond-Lemberty, 2018). Increasing the number of modeling nodes and connections, enabling micro-macro interactions, and allowing for multi-equilibria including system collapse all increase model complexity, as does representation of heterogeneity, nonlinearities, regime shifts, adaptive systems, ability to self-organize, cross-scale interactions, path dependence, and/or emergence properties.

On the other hand, while these model enhancements might improve realism, too much complexity can make models less useful and more difficult to interpret (Calvin & Bond-Lemberty, 2018). This is particularly true if the interactions are weak and highly uncertain (as discussed in Section 3.4). Of the feedbacks that are relevant, the representations of the systems and their linkages should be as simplified as possible (van Vuuren et al., 2012). Even when including complexity may be valuable (i.e., feedbacks are sufficiently well-understood and/or strong enough to warrant inclusion), this should be balanced against the costs of complexity, which include reduced transparency, increased difficulty in analyzing and interpreting model results, intractability, increased risk of error propagation, and increased computational needs (Calvin & Bond-Lemberty, 2018). As longer running times result in complex models being run less frequently, sensitivity analysis and robustness tests are often less extensive. As uncertainty analysis is critical in SES due to the importance of compound events (discussed in Section 3.3), this should also be weighed against complexity. With these factors in mind, many approaches to modeling SES are unnecessarily complex (Calvin & Bond-Lemberty, 2018).

As SES and CHANS literatures value these complexities, they often adapt agent-based modeling consistent with AB-IAMs over less sophisticated traditional models like SC-IAMs (An, 2012; An et al., 2014). The modeling advantages of AB-IAMs are numerous. They enable direct modeling of individual economic agents (moving away from the representative consumer); inclusion of additional social processes, social structures, norms and institutions, more realistic human behavior (i.e., relaxing neoclassical assumptions and replacing them with more empirically supported assumptions) and social structures; and heterogeneity in actors (including

their beliefs and access to information) and their interactions (An, 2012; An et al., 2014; Schlüter et al., 2012; Schlüter et al., 2017). In doing so, emergent properties, like unidentified thresholds, can arise (Miller & Morisette, 2014). The disadvantages of AB-IAMs are also significant: many modeling decisions without an agreed upon framework, protocols, or standards (Schlüter et al., 2012); many alternative models of decision making to neoclassical theory without a clear favorite (An, 2012; An et al., 2014; Schlüter et al., 2015; Schlüter et al., 2017);[24] lack of validation and verification techniques (An, 2012; Miller & Morisette, 2014);[25] lack of accessibility and transparency due to code complexity (An et al., 2014); data intensiveness for parameterization and calibration (An et al., 2014); and computation requires sequential solution procedures whose solution may significantly vary by operation order (An et al., 2014).[26] This latter shortcoming may be particularly problematic in climate models with long timeframes, as the impact of operation order increases over time (An et al., 2014). Even so, in favoring AB-IAMs, these interdisciplinary fields clearly believe that these advantages outweigh the costs for their purposes of understanding SES and analyzing resilience.

The weight of benefits and costs differ by the respective purpose of the modeling exercise. For purposes of policy analysis, and specifically improving the estimate of the SCC, the complexity of AB-IAMs may be less desirable. In the United States, adoption of heterodoxic, non-standard assumptions advocated for in ecological macroeconomics may lead to a rejection of the model by policymakers. Difficulty in verification, particularly of emergent properties (see Section 3.6), makes their use in policy less valuable. Furthermore, in comparison to SC-IAMs' three-decade history and one decade use in United States policy, AB-IAMs are only recent additions to the literature with many author-driven assumptions (i.e., many relevant modeling decisions) yet to be explored. This coupled with their lack of transparency and accessibility may further undermine policymakers' trust. In terms of policy use, AB-IAMs are also more specifically designed to test policies that improve system stability and avoid collapse (i.e., identify leveraging opportunities like focusing events that create socially beneficial positive feedback loops) than estimate the social cost of carbon (Beckage et al., 2018), though estimating of carbon taxes is possible.[27]

Instead, modelers may want to modify existing policy optimization and evaluation IAMs. Despite allowing for less complexity, particularly on the social side, social-cost and detailed-structure IAMs can still capture many of the necessary complexities. In fact, these models are capable of explicitly including interactions, feedbacks, and stochasticity. Other features may be represented implicitly. Given their existing application in policy use, applying modified versions of these models will aid policymakers in accepting the inclusion of climate-society feedbacks.

3.6 Lesson 6: Emergent properties need to be tested

A shortcoming of agent-based IAMs is the difficulty of verification – this is particularly true for emergent properties. As mentioned earlier, AB-IAMs can produce surprise dynamics; this is one of their strengths in highlighting currently unknown dynamics (An et al., 2014). However, it is often unclear if these surprises are a revelation of complex, real world dynamics or merely an artifact of the model. Verification of these effects, however, is often not possible except in some easy to detect cases (An et al., 2014). Nevertheless, AB-IAMs can be useful in pointing towards policies that reduce systematic risk and highlight directions for future research to identify key risks (Miller & Morisette, 2014).

3.7 Lesson 7: A suite of models is necessary to study the climate-society system

As noted in Section 3.1. there are many modeling alternatives available (Schlüter et al., 2012). In some cases, it is unclear if many of the interdisciplinary models are well suited for addressing policy issues (Schlüter et al., 2012), such as setting the social cost of carbon. But academic disciplines and policymakers need not select one

[24] There are 30 or more alternative (and competing) models of decision making (Schlüter et al., 2017; An, 2012)
[25] Recently, some validation protocols have been introduced (An et al., 2014).
[26] When developing an AB-IAM, modelers must test the impact of order of operations (An et al., 2014).
[27] For example, LAGOM (Lamperti et al., 2019) is a multi-agent AB-IAM that allows for multiple equilibria. Thus, it enables modelers to capture the impact of policies (or lack of policy) on the transition from one equilibrium to another. In doing so, LAGOM models climate change as a coordination problem.

modeling approach and wholly reject all others. Instead, fields should develop a variety of models. The primary value of this approach is to test whether modeling results and policy recommendations are robust across models and a variety of modeling specifications (Schlüter et al., 2012).

The three modeling approaches that we discuss can also inform each other. Detailed-structure IAMs have long history of producing inputs for SC-IAMs and reduced-form IAMs more generally (Weyant, 2017), as their higher levels of detail are well suited for measuring climate impacts by region and sector and for evaluating costs of mitigation and adaptation. As discussed in Section 3.1, linking social and climate models can be critical to understanding climate-society feedbacks (Calvin & Bond-Lamberty, 2018). Linking policy evaluation IAMs and earth-system models is especially useful (van Vuuren et al., 2012). Specifically, by linking policy evaluation models with earth system models to capture two-way interactions between emissions and human behavior, modelers can measure the emission changes from feedbacks. For example, using an earth system model, Peter Thornton et al. (2017) finds a negative feedback whereby increased crop yields from climate change (in RCP 4.5 and RCP 8.5) results in decreased agricultural land, increased forests, and increased competitiveness of biofuels. These emission change outputs can be used to calibrate reduced-form connections within SC-IAMs. Alternatively, agent-based IAMs are particularly well-suited for helping develop theories, particularly through their emergent properties (Boumans et al., 2015; Finn Müller-Hansen et al., 2017). Once validated through further study, these feedbacks can be integrated into policy-optimization models, like SC-IAMs.

3.8 Lesson 8: New data is necessary to identify feedbacks

New data are necessary to calibrate more sophisticated versions of all three models and empirically estimate feedback effects.

The various statistical strategies required to identify and measure climate-society feedbacks require new data. Statistical strategies could include reduced-form seemingly unrelated regressions, as used in vehicle literature (Kenneth Small & Kurt Van Dender, 2007; Kent Hymel et al., 2010). Alternatively, causal identification may require researchers to examine each leg of a causal loop, a task that will often require access to multiple datasets, given that many of these feedbacks vary across temporal, spatial, and hierarchical scales.

AB-IAMs, linked detailed-structure IAMs and earth system models, and research under the SES framework (Schlüter et al., 2012; Binder et al., 2013), also require access to unique datasets for the calibration of new and more sophisticated models, to verify emergent properties, and to specify the relevant SES variables (An et al., 2014; Palmer & Smith, 2014). For SES research, data will need to be collected at various spatial, temporal, and hierarchical scales and across various social and natural sciences. In some cases, this data may not be currently available and may require development. These data will also need to be integrated to make identification possible. Given the required combination of political, economic, ecological, climate, and other disciplinary datasets, we should expect this construction and integration to take time (Palmer & Smith, 2014).

3.9 Implications of Lessons: A modified SC-IAM is still the best way to estimate the SCC

We have highlighted three alternative modeling options for integrating climate-society system feedbacks into climate-economy models: agent-based IAMs, SC-IAMs, and the integration of earth system models with detailed-structure IAMs (Section 3.1). To select between these tools, the appropriate choice depends on the research question at hand (Miller and Morisette, 2014; Calvin and Bond-Lemberty, 2018). As discussed in Section 3.5, there are several reasons to prefer SC-IAMs for U.S. policy analysis: (1) a 10-year history of using SC-IAMs to calculate the SCC for U.S. policy (IWG, 2010) compared to no experience within even academic communities of calculating the SCC using detailed-structure or agent-based IAMs; (2) three-decade history of SC-IAMs; (3) U.S. policy generally favors neoclassical theory over heterodoxic economics, as they are the standard assumptions (An et al., 2012); (4) rationale behavior models are more well suited when estimating optimal outcomes, like emissions paths and taxes, as inefficient outcomes can result otherwise (Schlüter et al., 2017); (5) difficulty in validating results, particularly emergent properties, from AB-IAMs (Sections 3.5 and 3.6); (6) loss of tractability, accessibility, and transparency with further complexity, and (7) climate-society feedbacks are highly uncertain despite the potential of being significant making more complex integration less valuable (Section 3.4). Overall, in the balance of simplicity, acceptance to policymakers, and ability to capture important climate-society system dynamics, improving SC-IAMs to better represent inter-systems dynamics holds out

substantial promise to better inform policymaking in the near term. Even so, additional scholarly work in the areas of agent-based IAMs and integrated earth system models with detailed-structure IAMs is also justified to continue to refine and improve these approaches, even if the short-term policy impact may be more muted.

4. Integrating Climate-Society Feedbacks into SC-IAMs

In Section 2.1, we developed a taxonomy for feedback effects for purposes of integrating them into SC-IAMs. Specifically, we separated climate-society feedbacks from environmental and social feedbacks. We then discussed various types of climate-society feedbacks (see social sector and feedback element in Table 1). To integrate climate-society feedbacks into SC-IAMs, we need to further subdivide our taxonomy by the environmental nodes represented in SC-IAMs' climate system (see Table 2) and feedback mechanism (see mechanism in Table 1).

In our taxonomy, we divide environmental interactions into two groups: climate and non-climate. We define climate interactions as those explicitly or implicitly represented within SC-IAMs' climate equations making our definition differ slightly by the SC-IAM applied. Using these definitions, we define six types of climate-triggered feedback effects: (1) climate feedbacks captured in the climate system of SC-IAMs; (2) climate-triggered non-climate feedbacks that directly impact human welfare through SC-IAM's damage function; (3) social feedbacks as defined by Kopp et al. (2016) (e.g., migration); (4) climate-society feedback effects covered in Table 1; (5) climate-non-climate feedback effects frequently associated with runaway climate change; and (6) social-non-climate feedback effects, which are traditional SES triggered by climate change, also implicitly captured by the damage function. Each of these tipping points can be implicitly or explicitly represented in SC-IAMs, though we focus in this section on how to integrate climate-society feedbacks into SC-IAMs using reduced-form equations consistent with the aggregate structure of SC-IAMs.

For integration, we can further classify the climate-society feedbacks in Table 1 by their potential mechanism within SC-IAMs.[28] Specifically, we identify eight pathways for climate-society feedback effects in DICE-2016R: temperature to emission intensity ratio; temperature to backstop price; temperature to GDP; temperature to pure rate of time preference; mitigation to emission intensity ratio; temperature to land emissions; temperature to elasticity of marginal utility of consumption; and mitigation to backstop price.[29] We also identify six additional mechanisms from either earlier versions of DICE/RICE or the other two most cited SC-IAMs (FUND and PAGE) including: sea level rise to emission intensity ratio; adaptation to emission intensity ratio; regional temperatures to emission intensity ratio; regional populations to emission intensity ratio; migration to backstop price; and temperature to fraction of emissions in control regime. These mechanisms can be translated directly into a simple equation representing feedback effects from one specific node in the model to another. The magnitude of each mechanism's effect is the sum of all feedback effects that can be approximated by that mechanism similar to the enumerative method for constructing damage functions. The selected functional form approximates the underlying aggregate relationship, though a polynomial approximation is ideal when aggregating across many feedback effects if estimates of feedbacks are available at

[28] There are several frameworks that can inform our mechanism taxonomy, each of which essentially categorizes feedback effects by the nodes that they impact. Kopp et al. (2016) classifies environmental tipping points by the environmental components they will impact: global/regional temperature and precipitation, global and regional sea level rise, greenhouse gas emissions, albedo, and ecosystem services. Likewise, they categorize social tipping points by the social components they will impact: economic welfare, environmental policy, adaptation/vulnerability, and greenhouse gas emissions. Alternatively, Woodward et al. (2019) uses the Kaya identity to categorize potential drivers of climate-society feedbacks: population, GDP per capita, and emissions-output ratio (the product of energy intensity and carbon footprint of energy). Finally, NAS (2017) uses a modular framework to divide SC-IAMs referring to feedbacks between these modules: socioeconomic (GDP); population; emission – industrial emissions, land use emissions, and exogenous forcing; climate (earth system model – atmosphere, oceans; sea level rise; and ocean acidification); damages; and social welfare (utility function and preference parameters). We build on these taxonomies by classifying our feedback by the reduced-form way it will be modeled: the origin node (usually global mean temperature) to the destination node.

[29] Technically, there is one additional pathway for climate-society feedback effects in DICE-2016R. For adaptation technology, a positive learning by doing feedback effect can arise. However, this feedback effect should be implicitly captured by DICE's net damage function and explicitly captured in the existing adaptation cost function in PAGE.

multiple temperature levels. The value of this reduced-form approach is that it maintains the simple aggregate structure of SC-IAMs, while adding some additional realism regarding feedback effects. Using simple representations of feedback effects in SC-IAMs also helps ensure tractability. Adding a small amount of complexity to SC-IAMs in this manner helps maintain the transparency of SC-IAMs,[30] a critical strength of SC-IAMs for use in policy analysis, ensuring a clear estimate of the SCC in line with National Academy of Sciences (2017) goals.

The most critical of the feedback effects to incorporate into DICE is temperature to the emission intensity ratio (i.e., the amount of CO_2 per unit of GDP), as it is by far the most common mechanism in Table 1. In addition to temperature, the emission intensity ratio can also be modeled as function of mitigation in DICE and sea level rise, adaptation, regional temperatures, and regional populations in the other SC-IAMs. In DICE, the emissions output ratio declines over time on an exogenous path, partially driven by private and federal research and development and potentially learning by doing (Howard & Livermore, 2019). Climate drivers, like temperature, impact this ratio through their impacts on the production/consumption good mix, available and adopted emissions technologies (including adaptation and mitigation technologies), private and government funds available for research and development of technologies, and the energy and transportation mixes (Howard & Livermore, 2019). By the Kaya identity, we can split the emission intensity ratio into the product of energy intensity and the carbon footprint of energy. Given the importance of emission intensity for feedbacks, it is worthwhile to modify DICE in the future to focus on each of these two subcomponents and their corresponding feedbacks separately (Woodward et al., 2019).

The second most common mechanism is the impact of temperature on the price of the backstop technology. The backstop price can also be modeled as a function of mitigation (and migration in FUND) in addition to temperature. The backstop technology either takes CO_2 out of the atmosphere completely (e.g., carbon sequestration) or is a zero-emission technology (Nordhaus & Paul Sztorc, 2013). In DICE, the price of the backstop technology declines over time on an exogenous path as these technologies improve, partially via private and government research and development and learning by doing. Due to investment spillovers, climate drivers positive or negatively affect the backstop price by worsening or improving, respectively, R&D through government cooperation: treaties, cultural tightness, and focusing events. Climate drivers can also impact learning by doing via adoption of mitigation technology.

Only two other feedback mechanisms in DICE-2016R include multiple elements. Temperature to GDP is an important mechanism already captured by all versions of DICE. In addition to the direct impact of temperature on GDP, GDP can also be modeled as a function of mitigation, as in all versions of DICE, and adaptation. In the case of capturing conflict-development traps, the inclusion of a nonlinearity is necessary. Specifically, it may be crucial to introduce a GDP level at which the trap becomes probable in a manner similar to how PAGE09 models environmental tipping points. Another important mechanism is temperature to preference parameters, as worsening climate change increases perceived risks of extinction and triggers human preference adaptation. In both cases, climate drivers impact the pure rate of time preference or the elasticity of marginal utility of consumption (e.g., endogenous risk aversion). For the former parameter, the pure rate of time preference can be modeled as a decreasing function of consumption (i.e., decreasing marginal impatience) (Jayanta Sarkar, 2007; Luis Alcalá et al., 2019), such that the climate damage function directly impacts time preferences.[31] Alternatively, the pure rate of time preference can be modeled as a direct function of temperature, a function of accumulated patience (and additional state variables), or a hazard rate can be included directly impacted by temperature (Stern, 2006; Tsur & Zemel, 2009). For the latter parameter, modelers can build on the endogenous risk aversion literature, as the elasticity of marginal utility of consumption in the Ramsey framework applied by SC-IAMs is simultaneously the preference parameter for "consumption smoothing,

[30] Part of SC-IAMs' transparency stems directly from their aggregate structure that makes interactions clear and observable (Michael Roos, 2018).

[31] To ensure a unique (optimal) solution, the elasticity of the marginal utility of consumption must be greater than one (Giuseppe Di Vita, 2012).

inequality aversion, or risk aversion" (Ben Groom & David Maddison, 2019). In the case of endogenous preference parameters, modelers should take care to ensure a time-consistent solution (Stern, 2006).

Finally, temperature to land emissions is critical to capturing feedback effects that arise from land use changes. Climate-driven price and yield changes can trigger emission changes captured by the land emission variable in DICE-2016R. Additionally, fire, storms, and other climate drivers can lead to lost forests, a potential environmental tipping point (Kopp et al., 2016), and shifting (vegetation) species distributions (Mike Austin & Kimberly Van Niel, 2011; Jens-Christian Svenning & Brody Sandel, 2013). These changes may alter human behavior leading to additional landcover based emission changes.

Previous versions of the DICE/RICE model enable the additional integration of feedback effects. Most notably, DICE-2013R explicitly modeled the fraction of emissions in the control regime. Thus, it enables modeling of political feedback effects whereby temperature increases decrease the number of nations committed to climate action via focusing events, treaties, and/or cultural tightness. Howard and Livermore (2019) explicitly demonstrated that this potential pathway for political feedback effects can greatly impact emission levels. Additionally, DICE-2010 explicitly models sea-level rise instead of implicitly accounting for sea-level rise damages in the traditional DICE damage function that measures only the impact of temperature on GDP (Nordhaus & Boyer, 2000). This allows sea-level rise to directly impact emission intensity, a mechanism driven by adaptation behavior. Finally, RICE (like FUND and PAGE) explicitly models economic regions instead of one aggregate global region, a key driver of migration feedbacks. Including regions also allows modelers to estimate the feedback mechanism of regional temperatures on emission intensity. If these feedbacks are important, these alternative modeling strategies can be re-introduced into the most up-to-date version of DICE to enable the inclusion of the relevant mechanism.

Instead of explicitly modeling feedbacks, some climate-society feedbacks require alternative calibrations of the DICE model. For example, learning by doing implies endogenous technical change for adaptation and mitigation technologies. To represent endogenous technical change in DICE, adaptation can be explicitly modeled – as PAGE,[32] WITCH, AD-DICE, and AD-MERGE – as can learning by doing – as in the hybrid IAMs MERGE and WITCH – though empirical issues can arise (Nordhaus, 2014). Alternatively, modelers can adjust the DICE damage function to implicitly account for the adaptation portion of this feedback effect, as adaptation and its costs are implicitly captured in the older, enumerative based damage function (Howard, 2014). This type of adjustment is not possible with the current meta-analysis-based damage function (Nordhaus, 2017), as it is unclear to the extent that adaptation and its costs are captured.

Despite some additional complexity, DICE can remain tractable with the inclusion of these feedback effects. In this paper, we do not engage in these modeling exercises. We recognize that these adjustments will require empirical estimates, aggregation, and modeling. In doing so, computational difficulties and tractability will need to be overcome. However, in an earlier paper (Howard & Livermore, 2019), we demonstrate three potential mechanisms for political feedbacks: temperature to emission intensity ratio; temperature to backstop price; and temperature to fraction of emissions in control regime. Specifically, we abstractly modeled these feedback effects as a flatting of their three exogenous curves in DICE with the crossing of the 2°C temperature limit. We find that the mechanism where temperature impacts participation in international mitigation efforts can greatly impact the optimal temperature and GDP, though the results are sensitive to the level of global participation after the 2°C limit is breached. In this modeling exercise, we overcame the issue of tractability from a discrete change by using continuous approximations, as inspired by Nordhaus' representation of environmental tipping points in DICE-2013R (Nordhaus, 2013).

Recently, some SC and hybrid IAMs have implemented a similar strategy as Howard and Livermore (2019) using emulators of more complex models to calibrate reduced-form feedback effects. In PAGE-ICE, Yumashev et al. (2019) approximates two complex climate feedbacks – permafrost carbon and surface albedo – using emulators that essentially create a simple representation of additional greenhouse gases as a function of temperature. In the hybrid IAM WITCH (Emmerling et al., 2016), developers include a land use sector by

[32] Thus, it is possible in PAGE to explicitly model the impact of adaptation adoption on future adaptation costs (Howard, 2014).

emulating the GLOBIUM model using a calibrated reduced-form response function. This allows WITCH to model the impact of carbon and biomass prices on land use, biomass production, and land emissions and mitigation. However, while WITCH captures the percentage loss of GDP from reduced agricultural yields in its damage function, reduced yields do not feed back into GLOBIUM limiting WITCH's ability to fully capture climate-social feedbacks emerging from land use change (Emmerling et al., 2016).[33] Similar or modified approaches could be implemented in DICE. However, unlike PAGE-ICE, which represents the permafrost carbon and surface albedo feedbacks separately, we recommend combining all feedback effects with the same nodes and approximating the resulting aggregate feedback effect with a Taylor approximation.

Similar solutions will be necessary for modeling alternative types of feedback effects, particularly as multiple feedbacks are included to capture interactions.

5. Conclusion

Research into climate-society feedbacks is necessarily interdisciplinary and spans natural sciences (such as ecology and earth system sciences) and multiple social science disciplines (economists, sociologists, psychologists, and political scientists). Many of these fields are already at the forefront of developing interdisciplinary fields of studies on these issues, including SES and CHANS. In this paper, we highlight key lessons from these literatures for economists, as it is critical that climate-economy policy models account for these additional feedback risks. Due to reasons of simplicity and transparency, tractability, and modeling history (with respect to the social cost of carbon), we find that there are reasons for economists to update SC-IAMs to included climate-society feedbacks instead of replacing the modeling approach altogether with more complex models like agent-based IAMs. To advance this goal, we build a taxonomy of climate-society feedbacks to aid their inclusion in SC-IAMs. We then apply this taxonomy to existing feedbacks identified in the literature to demonstrate this taxonomy and highlight key feedbacks. Our results should not be taken as a rejection of AB-IAMs and other climate-economy models. Instead, economists should also advance these models to identify feedbacks, estimate their magnitude, and test the robustness of SC-IAM results with respect to the SCC and optimal policy and climate trajectories. Due to their differing capabilities, AB-IAMs are also better situated for testing the stability of the climate-economy system and identifying opportunities for system-wide transitions.

To identify feedback effects, data will need to be constructed across disciplines and scales (temporal, spatial, and hierarchical). Researchers can either estimate each step in a causal use diagram or they can attempt to estimate aggregate reduced-form feedback equations. These identification strategies can be coupled with use of the SES framework and agent-based IAMs to identify potential climate-society feedbacks, though empirical testing is still necessary for confirmation. Coupled earth system-detailed-structure IAMs have already been used to estimate the magnitude of land use feedback effects; these models should be used more in the future for identifying the magnitudes of other climate-society feedbacks. Economists can use these various estimates to calibrate reduced-form climate-society feedback equations.

The various fields involved in the study of climate-society feedbacks should acknowledge several critical lessons to ensure that IAMs and climate policy instruments, like the social cost of carbon, account for climate-society feedbacks. It is critical that empiricists and modelers keep IAMs in mind when developing their projects and at publication. In the past, IAM developers have lamented the difficulty of integrating key climate damage research into their models due to lack of sufficient geographic coverage and lack of welfare estimates. Economists and researchers involved in SES and CHANS research overlapping with climate-society feedbacks should account for potential difficulties in integration if they hope to directly influence policy instruments. Additionally, it is critical that empiricists and modelers use a common vocabulary. It may be necessary to develop a separate or overlapping vocabulary for climate-society feedbacks to ensure that IAM developers find

[33] Bosello and Enrica De Cian (2014) estimate climate damages for agriculture using ClimateCrop and for increased energy demand using the POLES model, though the resulting impacts are fed into ICES to calculate damage estimates (as a % of GDP) and not into the land use or energy sector models. Consequently, agricultural yields in WITCH vary by climate scenario, land quality, and fertilizer application following GLOBIUM, not by temperature. Thus, WITCH can capture some land-use feedbacks from increased demand for biomass and carbon sequestration, though not those resulting from declining or increased yields leading to land use change and changes in net emissions.

the relevant research to calibrate feedback equations in their models. From our experience, collecting this empirical work is difficult and currently requires informal, rather than formal, searches and selection methods.

Finally, it is critical that economists and other social society system researchers engage with the legal and policy field beyond merely improving policy instruments, like the social cost of carbon. Legal institutions can be designed to be robust to climate-society feedbacks that would otherwise lead to catastrophic events. Law and policy can also be constructed to reduce the probability of key negative events or reduces risky connections, and can also attempt to leverage beneficial feedback effects that could lead the economic system on a more sustainable path. It is critical that we bridge this gap between the legal and policy fields and researchers of climate-society systems.

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Table 1. Climate-Society System Feedbacks, by element, direction, and model pathway

Social Sector	Feedback Element	Direction	Main Impact Pathway	Mechanism	Key Reference
Adaptation	Running adaptation technology	Positive	Energy demand for adaptation technology (e.g., heat and cooling electricity demand, desalinization, etc.)	Temperature to emission intensity ratio; Adaptation to emission intensity ratio (in PAGE)	Tol, 2013; van Vuuren et al., 2012; Auffhammer and Mansur, 2014; van Ruijven et al., 2019
	Migration	Positive	Relative emission intensity	Temperature to emission intensity ratio; Sea level rise to emission intensity ratio (in DICE-2010); Regional populations to emission intensity ratio (in RICE, FUND, and PAGE)[A]	-
	Building adaptation technology	Positive	Emissions from building adaptation technology (e.g., GHG emissions from seawalls)	Temperature to emission intensity ratio; Sea level rise to emission intensity ratio (in FUND, PAGE, and DICE-2010); Adaptation to emission intensity ratio (in PAGE)	-
Behavioral	Transportation	Positive	Driving in warmer weather	Temperature to emission intensity ratio	Obradovich and Rahwan, 2019

Production	Agent re-optimization	Negative	Investment (declining funds available via net damages and reoptimization of savings rate)	Temperature to GDP	Nordhaus, 1994; Calvin and Bond-Lemberty, 2018; Bosetti, 2021
	Conflict-development trap	Negative	Investment (declining funds available via net damages and reoptimization of savings rate)	Temperature to GDP	Woodward et al., 2019; van Ginkel et al., 2018; Kopp et al., 2016
	Land use change	Uncertain	Land use change from price and yields changes	Temperature to land (including deforestation) emissions	Thornton et al., 2017; Calvin and Bond-Lamberty, 2018; Calvin et al., 2019; John Reilly et al., 2012
	Transportation	Uncertain	Commercial transportation change (e.g., changes in trucking or shipping routes)	Temperature to emission intensity ratio; Regional temperatures to emission intensity ratio (in FUND and PAGE	van Vuuren et al., 2012
Energy	Energy demand	Positive	Energy demand for adaptation (e.g., heat and cooling electricity demand) and mitigation	Mitigation to emission intensity ratio; Adaptation to emission intensity ratio (in PAGE)	Tol, 2013; van Vuuren et al., 2012; Auffhammer and Mansur, 2014

	Thermal power	Positive	Decreased thermal-efficiency and water availability	Temperature to emission intensity ratio	Mideksa and Kallbekken, 2010; van Vuuren et al., 2012; Cronin et al., 2018
	Renewables	Uncertain	Impact on efficiency of bioenergy, hydro, solar, and wind	Temperature to emission intensity ratio	Mideksa and Kallbekken, 2010; Cronin et al., 2018
	Transmission	Positive	Rising temperatures and storms	Temperature to emission intensity ratio	Mideksa and Kallbekken, 2010; Cronin et al., 2018
Technology (Emission Intensity and Backstop Technology)	Mitigation	Positive	Energy demand for mitigation (backstop) technology	Mitigation to emission intensity ratio	van Vuuren et al., 2012
	Learning by Doing	Negative (mitigation)/ Positive (adaptation)	Endogenous technical change	Mitigation to backstop price; Adaptation to adaption cost (implicit via damage function in DICE and explicit via adaptation cost function in PAGE)	Michael Grubb et al., 2002; Terry Barker et al., 2006; Pierre-André Jouvet and Ingmar Schumacher, 2012; Kopp et al. 2016

	Cooperation	Uncertain	Reduced R&D for emissions and backstop technologies	Temperature to emission intensity ratio; Temperature to backstop price	Howard and Livermore, 2019
Political	Focusing events	Negative	Environmental policies (GHG intensity); perceived risk and beliefs about policy efficacy (Beckage et al., 2018); cooperation (i.e., fraction of emissions in control regime); technology R&D (GHG intensity and backstop technology) (Howard and Livermore, 2019)	Temperature to emission intensity ratio; Temperature to backstop price; Temperature to fraction of emissions in control regime (in DICE-2013R)	Jarvis et al., 2012; Kopp et al. 2016; Beckage et al., 2018
	Cooperation	Positive	Cooperation (i.e., fraction of emissions in control regime); technology R&D (GHG intensity and backstop technology); environmental policies (GHG intensity)	Temperature to emission intensity ratio; Temperature to backstop price; Temperature to fraction of emissions in control regime (in DICE-2013R)	Howard and Livermore, 2019
	Democracy	Positive	Cooperation (i.e., fraction of emissions in control regime); technology R&D (GHG intensity and backstop technology); environmental policies (GHG intensity)	Temperature to emission intensity ratio; Temperature to backstop price; Temperature to fraction of emissions in control regime (in DICE-2013R)	Sequeira and Serra Santos, 2018; Hu et al., 2021

	Cultural tightness	Positive	Cooperation (i.e., fraction of emissions in control regime); technology R&D (GHG intensity and backstop technology); environmental policies (GHG intensity)	Temperature to emission intensity ratio; Temperature to backstop price; Temperature to fraction of emissions in control regime (in DICE-2013R); Migration to backstop price (in FUND)	Jackson and Michele Gelfand, 2019; Jackson et al., 2019; Hu et al., 2021
Preferences	Human preference	Uncertain	Human preferences adapt, making them time variant and/or endogenous	Temperature to pure rate of time preference; Temperature to elasticity of marginal utility of consumption	Schlüter et al., 2012; Donges et al., 2018
	Perceived risk of extinction	Negative	Endogenous pure rate of time preference or modify social discount rate by adding hazard rate that is a function of aggregate emissions	Temperature to pure rate of time preference	Beckerman and Hepburn, 2007; Tsur and Zemel, 2009; Alcalá et al., 2019.

[A] In FUND, the impact of climate change on regional populations is captured by explicitly modeling migration. In RICE and PAGE where migration is not modeled, a reduced-form mechanism must be included whereby regional populations are a function of temperature and/or sea-level rise.

Table 2. Taxonomic matrix for classifying feedback effects between subsystems in SC-IAMs.

Earth Subsystems	Environmental: Climate (C)	Environmental: Non-Climate (N)	Social (S)
Environmental: Climate (C)	CC: Water vapor, cloud cover, snow cover, ice cover, and ocean carbon cycles[A]		
Environmental: Non-Climate (N)	NCN: Methane hydrates; permafrost;[B] amazon rainforest;[C] boreal forest	NN: Atlantic Meridional Overturning Circulation;[D] El Niño-Southern Oscillation;[D] Regional North Atlantic convection;[D] West African Monsoon;[D] Antarctic ice sheet; Greenland ice sheet; Coral reef	
Social (S)	SCS: see Climate-Society System Feedbacks in Table 1	SNS: SES studied by SES and CHANS that are triggered by climate change, but outside the scope of Climate-Society System Feedbacks (SCS)	SS: Migration, Endogenous technology, Conflict/development (as defined by Kopp et al. (2016))

[A] Part of NN in FUND, as FUND does not model ocean carbon cycles

[B] Part of CC in PAGE-ICE, as PAGE-ICE explicitly models permafrost.

[C] Part of CC in FUND, as FUND explicitly models amazon rainforest dieback

[D] Part of NCN in FUND and PAGE, as this feedback impacts regional temperatures that are explicitly modeled in FUND and PAGE

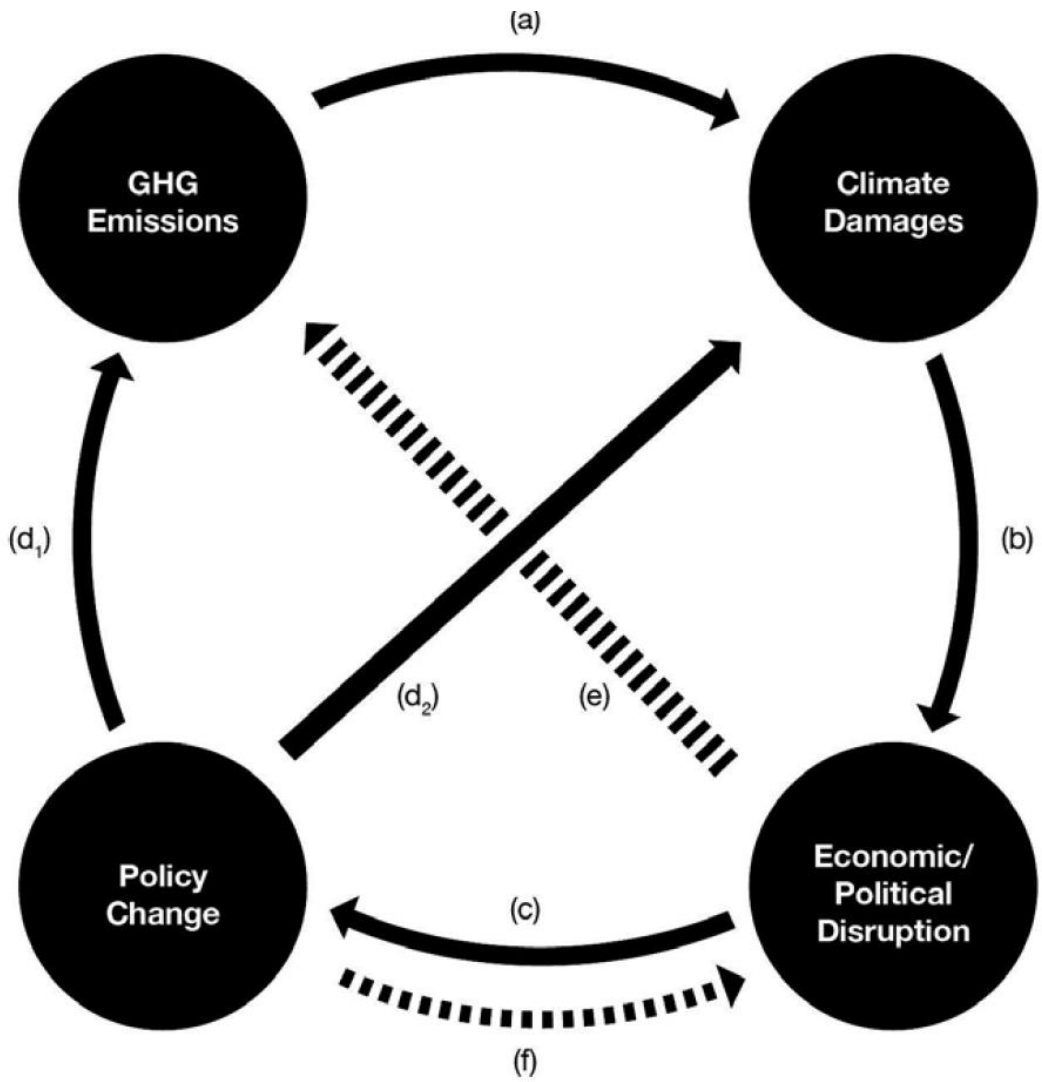

Figure 2. Relationships that drive an economic disruption pathway for sociopolitical feedbacks. **(a)** Greenhouse gas emissions lead to climate damages, such as reduced agricultural productivity. **(b)** Some climate damages could result in economic or political disruption including political violence. **(c)** These disruptions could lead to policy changes, such as withdrawal or under-enforcement of a mitigation regime, or cession of adaptation activities. **(d)** The policy changes could, in turn, affect greenhouse gas emissions **(d_1)** or vulnerability to future climate change **(d_2)**. **(e)** Economic or political disruption could also directly affect greenhouse gas emissions, for example by dampening economic growth. **(f)** Finally, policy choices that result from economic or political disruption, such as a decision to enact trade barriers, might affect the future likelihood of further disruption.

Reprint from Howard and Livermore (2019)