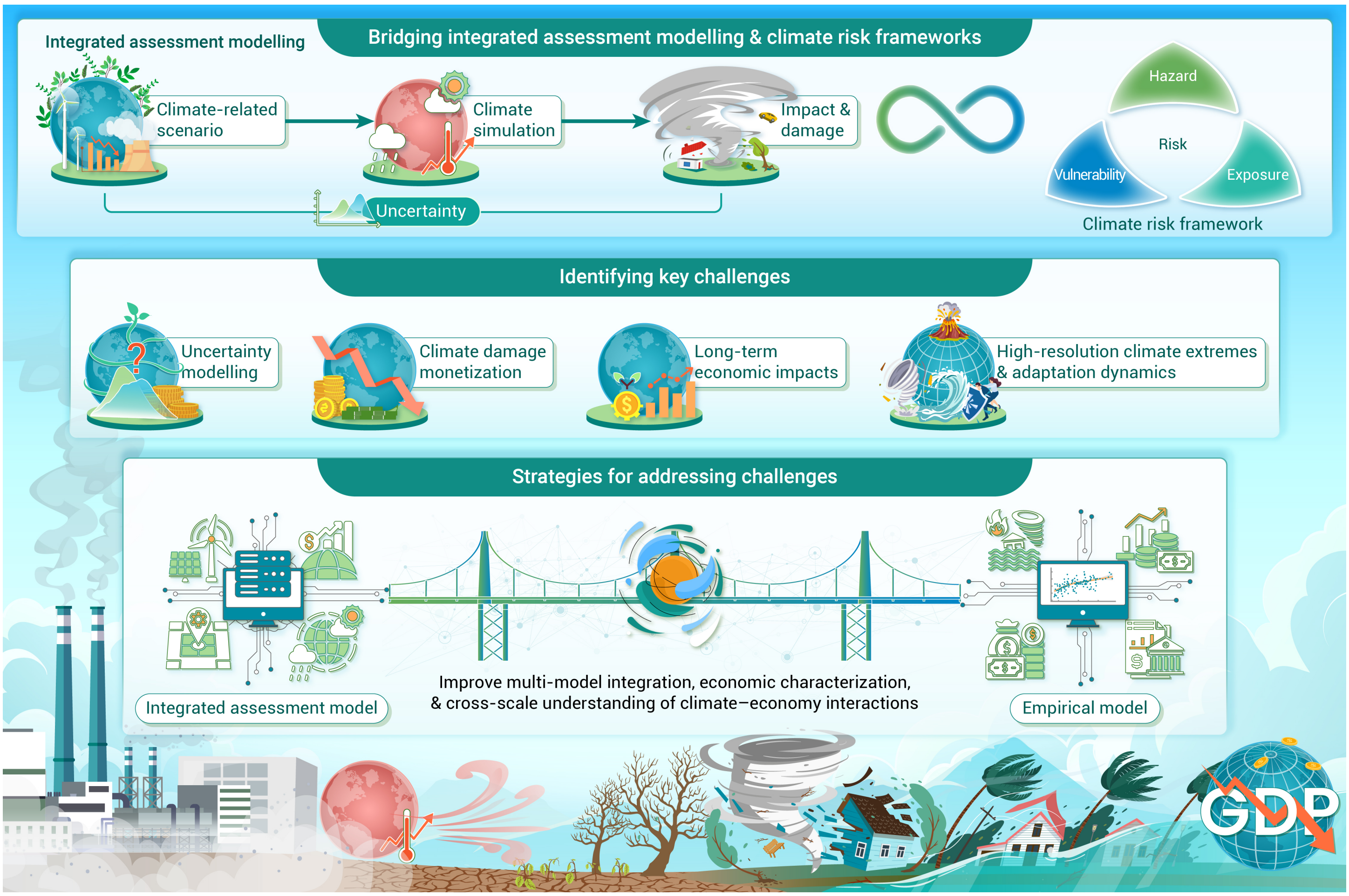
Assessing socioeconomic risks of climate change through integrated modelling

Jun-Jie Chang,[1,2,3,4,5,6] Zhifu Mi,[7,*] Biying Yu,[1,2,3,4,5,6] Xiao-Chen Yuan,[1,2,3,4,5,6] Bo Yang,[1,4] Si-Yu Liu,[1,4] Yu-Xiang Hu,[1,4] and Yi-Ming Wei[1,2,3,4,5,6,*]
*Correspondence: wei@bit.edu.cn (Y. W.); z.mi@ucl.ac.uk (Z. M.)
Received: May 30, 2025; Accepted: December 9, 2025; Published Online: January 21, 2026; https://doi.org/10.59717/j.xinn-energy.2026.100140

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Incorporate key elements of integrated assessment modelling into the Intergovernmental Panel on Climate Change (IPCC)'s framework of climate change risks.
- Investigate the integrated assessment tools for climate risks, highlighting their modelling features, scientific foundations, limitations and future directions.
- Identify key modelling challenges: uncertainty, climate damage monetization, long-term economic modelling, high-resolution climate extremes, and adaptation.
- Outline pathways to enhance models by bridging integrated assessment models (IAMs) and empirical models.

REVIEW Climate Risks

Assessing socioeconomic risks of climate change through integrated modelling

Jun-Jie Chang,[1,2,3,4,5,6] Zhifu Mi,[7,*] Biying Yu,[1,2,3,4,5,6] Xiao-Chen Yuan,[1,2,3,4,5,6] Bo Yang,[1,4] Si-Yu Liu,[1,4] Yu-Xiang Hu,[1,4] and Yi-Ming Wei[1,2,3,4,5,6,*]

[1]Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China
[2]Basic Science Center for Energy and Climate Change, Beijing 100081, China
[3]Beijing Laboratory for System Engineering of Carbon Neutrality, Beijing 100081, China
[4]School of Management, Beijing Institute of Technology, Beijing 100081, China
[5]Beijing Key Laboratory of Energy Economics and Environmental Management, Beijing 100081, China
[6]Joint International Research Laboratory of Carbon Neutrality System and Engineering Management, Beijing 100081, China
[7]The Bartlett School of Sustainable Construction, University College London, London WC1E 7HB, UK
*Correspondence: wei@bit.edu.cn (Y. W.); z.mi@ucl.ac.uk (Z. M.)

Received: May 30, 2025; Accepted: December 9, 2025; Published Online: January 21, 2026; https://doi.org/10.59717/j.xinn-energy.2026.100140

Citation: Chang J., Mi Z., Yu B., et al. (2026). Assessing socioeconomic risks of climate change through integrated modelling. *The Innovation Energy* **3**:100140.

Climate change poses significant socio-economic risks, necessitating integrated assessment modelling that bridges natural and socioeconomic systems to identify and manage climate risks. However, research on key components of integrated assessment frameworks remains fragmented across disciplines, lacking explicit integration with the theoretical framework of climate change risk. This hinders the practical application of integrated assessment approaches in climate risk management. In this narrative review, we synthesize key elements of integrated assessment modelling—climate-related scenarios, climate simulations, climate impacts and damages, and uncertainties—within the Intergovernmental Panel on Climate Change (IPCC)'s risk framework, defined by hazard, exposure, and vulnerability. We examine how these elements are represented in integrated assessment models (IAMs) and empirical approaches, highlighting their modelling features and scientific foundations. We identify critical challenges in current research, including (1) the treatment of uncertainty, (2) monetization of climate damages, (3) representation of long-term economic impacts, and (4) incorporation of high-resolution climate extremes and adaptation dynamics. We propose that addressing these gaps requires bridging IAMs and empirical methods to improve multi-model integration, economic characterization, and the understanding of climate–economy interactions across spatial and temporal scales.

INTRODUCTION

Climate change is already causing widespread socio-economic losses – from agriculture[1] and energy[2,3] to health[4] and infrastructure[5,6] – yet our understanding of these risks to human systems still lags behind our knowledge of the climate's physical impacts. These severe risks, spanning global,[7] regional,[8] national,[9] and local levels,[10] have far-reaching impacts on macroeconomics.[11] Their effects will persist for centuries, posing significant challenges to the sustainable development of humanity.[12] As previously demonstrated,[13-15] assessing climate change risks (Box 1 and Figure 1) can help decision-makers understand the extent to which climate mitigation strategies avoid climate risks (mitigation benefits), thereby helping them select the most cost-benefit economic mitigation pathway. It can also help decision-makers identify the demands for regional adaptation, enabling them to formulate climate adaptation strategies tailored to local conditions.

Assessing the risks that climate change imposes on the socio-economic system requires an integrated consideration of how the hazards are transferred from the climate system to the socio-economic system, which encompasses multidisciplinary knowledge such as physics, economics, management science, and geographical science. Therefore, it will be highly essential to integrate multidisciplinary knowledge and establish a consistent integrated assessment framework.[14,29] The current assessment paradigm can be summarized as the framework presented in Figure 2. It discloses the transmission mechanism through which the economic activity of human society gives rise to GHG emissions, which subsequently impact the climate system and the socio-economic system,[30-32] namely, Socio-economic pathways → GHG emissions → GHG concentrations → Radiative forcings → Climate-related hazards → Socio-economic damages. This transmission process fully embodies the three decisive factors of climate change risks: Firstly, the potential socio-economic pathways delineate the socio-economic characteristics such as the economy, population, energy structure, and policies, which determine the exposure and vulnerability. Secondly, diverse socio-economic pathways will generate distinct GHG emission pathways, thereby triggering differentiated pathways related to hazards. Thirdly, hazards will exert an impact and cause damage to different regions, sectors and communities within the socio-economic system. Different hazard-bearing entities will exhibit differentiated responses (vulnerability) when confronted with the shocks of the same hazards. Furthermore, factors such as future socio-economic development and policies are uncertain in both temporal and spatial dimensions, thereby rendering exposure and vulnerability uncertain as well. The uncertainty of the social economy will also give rise to the uncertainty of emission pathways. Once GHGs enter the climate system, there is uncertainty in the carbon cycle process within the climate system and climate sensitivity (the response of global mean temperature to emissions), ultimately resulting in climate-related hazards incorporating the aforementioned uncertainties. Under the combined effect of uncertain hazards, exposure and vulnerability, the socio-economic system will ultimately manifest the risks of climate change in the form of uncertain climate damages.

To sum up, the integrated assessment framework of climate change risks can be further refined into four key elements: climate-related scenarios, climate simulation, climate impacts and damages, and uncertainties. On the one hand, climate-related scenarios delineate potential climate transition pathways, thereby characterizing exposure and vulnerability. On the other hand, they can also depict the hazards under specific emission pathways. Climate simulation aims to investigate the effects of GHG emissions from the socio-economic system on hazards such as temperature, precipitation, sea level, and extreme events. Climate impacts and damages typically involve identifying the vulnerability of hazard-affected entities and combining it with hazard and exposure to assess the final risks caused by climate change. Uncertainty research is typically nested within the above-mentioned three key elements[17].

Although implicitly linked to hazards, exposure, and vulnerability, research on these four elements remains fragmented across disciplines, and the IAMs associated with them have primarily been explored within the realm of climate change mitigation rather than in the domain of Impact, Adaptation, and Vulnerability (IAV). However, existing research on hazards, exposure, and vulnerability has predominantly been situated within the IAV field. Limited research has explicitly linked key components of IAMs with the IPCC's framework of climate change risks to provide a systematic understanding of risk assessment. As global temperature rise approaches the critical 1.5°C threshold, reliance solely on climate mitigation measures proves inadequate to address escalating climate risks, necessitating the concurrent development of spatially targeted adaptation strategies. This imperative calls for paradigm integration between Mitigation and IAV to systematically address upcoming climate challenges. This integration would not only overcome the limitations of research methods based on specific disciplines and fields but also establish bridges for their cross-innovation, thereby providing more comprehensive scientific support for decision-makers in climate risk management.

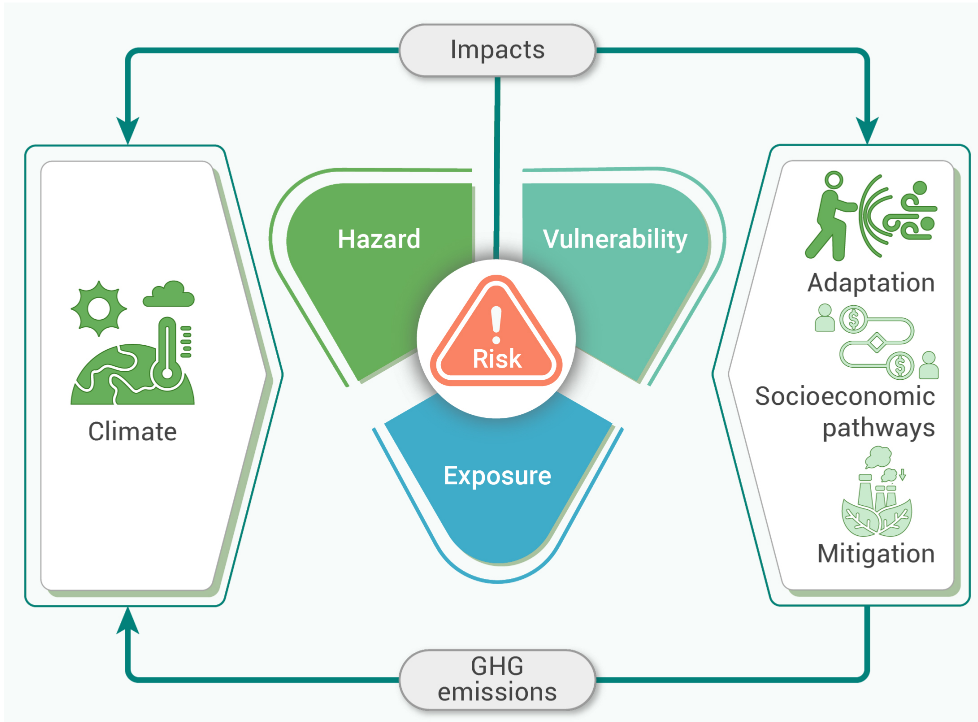


Figure 1. IPCC's conceptual framework of climate change risks (adapted from IPCC[28]).

Box 1. Defining climate change risk

The risks can be defined as potential adverse consequences for humans or ecosystems. In the conceptual framework of the IPCC,[16] climate change risks arise from the potential impacts of climate change. They also arise from the dynamic interaction between climate-related hazards and the exposure and vulnerability of the affected human or ecological system to such hazards. Hazard refers to potential physical events or trends caused by nature or humans, which may cause damage to property, health, infrastructure, etc. Climate-related hazards encompass extreme events such as heat waves, floods, and other "acute" hazards;[17-21] it also comprises some "chronic" hazards such as global warming and sea level rise.[22] The alterations of hazards mainly stem from human-induced climate change[23] and are directly affected by greenhouse gas (GHG) emissions. Therefore, controlling the emission pathway of GHGs through mitigation measures can effectively manage the hazards. Exposure refers to the objective existence of humans, infrastructure, economy, society, etc. These objective existences might be adversely impacted by climate-related hazards at a specific temporal-spatial level.[24] Exposure will be jointly determined by the hazards and socio-economic conditions, etc. For instance, in coastal regions, a more powerful hurricane is likely to have a broader impact on people and property compared to a less powerful one.[25] Urbanization will modify the population and asset value in exposed areas.[26] Vulnerability refers to the propensity of humans and assets to be negatively affected by climate change. It reflects the sensitivity of humans and assets to adverse effects and also the lack of ability to adapt to negative impacts. Therefore, adaptation measures can effectively modify the vulnerability of exposed entities.[27] Vulnerability is jointly shaped by socio-economic assets, socio-economic structures, as well as the climate and environment, and it fluctuates by geographical features, economic sectors, socio-economic characteristics, etc. Additionally, there exists uncertainty in hazard, exposure, and vulnerability, and they undergo alterations due to changes in the socio-economy and human decisions (risk response actions such as mitigation and adaptation). In light of the uncertainty and dynamic nature of these risk determinants, the quantitative assessment of climate change risks is to generate probability distributions for potential consequences of climate change impacts.

In this review, we conducted a targeted search of Web of Science, Scopus, and Google Scholar over 2010–2025. Searches centred on IAMs, IPCC risk framing, scenarios, climate modelling, climate–economy impacts, and uncertainty. We included peer-reviewed studies that provide empirical evidence or modelling implications related to them; Screening was supplemented by backward/forward citation chasing. Evidence was synthesised concept-centrically by theme, distinguishing convergent findings from contested ones and mapping them to the IPCC risk dimensions and to the transmission mechanism in Figure 2. Coverage is selective by design. We synthesise the evidence scattered in the research field of mitigation and IAV related to four elements—climate-related scenarios, climate simulation, climate impacts and damages, and uncertainty—within the IPCC risk framework (hazard, exposure, vulnerability) and the Figure 2 chain, thereby providing a more comprehensive understanding of assessing climate change risks at the socio-economic level.

We initially summarize the characteristics and application scenarios of the main tools for the integrated assessment of climate change risks, compare the advantages and disadvantages of different tools, and identify their correlations. Secondly, we summarize five types of key uncertainties and analyze how they are reflected in climate-related scenarios, climate simulations, and climate impacts and damages. Thirdly, we sort out the composition and construction process of climate-related scenarios and reveal how they are applied in risk assessment. Then, we analyze how to combine traditional climate simulations in natural science with the integrated assessment modelling of climate change. Finally, we summarize the characteristics of IAMs and empirical models when modelling climate impacts and damages and analyze the commonalities, differences, and connections of the two types of tools. The related scientific mechanisms and controversies are also identified and discussed in this section. Besides, throughout all sections, we identify the related limitations, potential challenges, and future trends and provide suggestions for modelling improvement.

TOOLS FOR RISK ASSESSMENT

The tools utilized for evaluating the risks of climate change comprise IAMs and climate econometric models.[17-19,33] IAMs are defined as a type of model that integrates knowledge from two or more domains within the same and

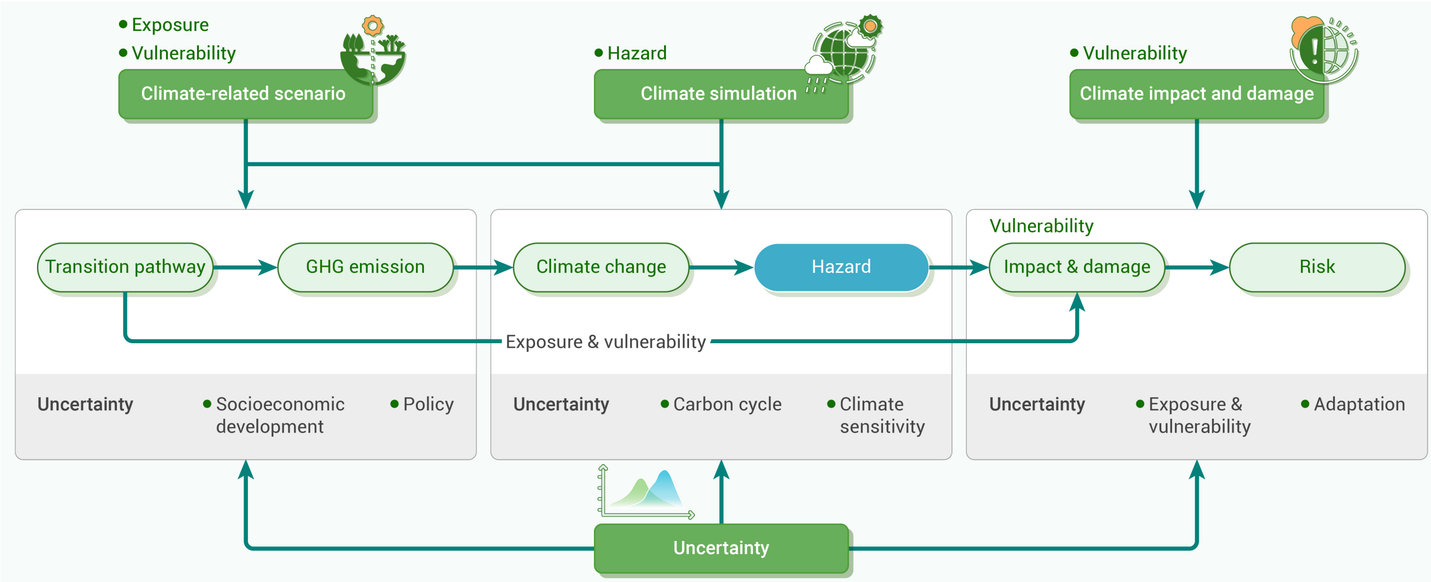


Figure 2. Integrated assessment framework of climate change risks

consistent framework.[34] These models typically incorporate the submodules related to the economy, energy system, climate simulation, land use, and climate damage.[32,35,36]

Through the economic dynamics module, IAMs can generate mitigation (transition) scenarios, the associated emission pathways, and the corresponding mitigation costs. On the one hand, this module can be modelled as a highly integrated and simplified single economic sector, such as the economic module of the DICE model.[37] On the other hand, this module can also be modelled in a more detailed manner. For instance, sectors are refined and modelled through general (partial) equilibrium models.[32,36] Such models reflect the interaction processes among various components in the macroeconomic system, such as C^{3}IAM/GEEPA[14]; in addition, the details of energy technologies can also be modelled through energy system models,[32,35,36,38] such as REMIND[39], which depict the deployment and costs of energy technologies, as well as the relationships between the supply side and the demand side in the energy system.

The climate impact and damage at the socio-economic level within IAMs are typically modelled through a series of damage functions in reduced forms (linear, quadratic, exponential, etc.), such as those in IAMs like DICE, RICE, FUND, PAGE, etc.[18] They typically parameterize the complex process of climate impact transmission and integrate the net impacts of climate change in specific regions and sectors. Alternatively, this module can also be modelled by process-driven climate impact models, which describe in detail the biophysical and economic processes. For instance, process-driven IAMs such as GCAM,[47] IMAGE,[48] MERGE,[49] etc.

Overall, the existing IAMs can be classified into two categories: process-driven IAMs and cost-benefit IAMs,[35,36] both of which are capable of generating emission pathways of GHGs and computing the associated mitigation costs. Process-driven IAMs can elaborate on the energy system, economic sectors, land use, and climate impacts in detail. Taking into account the driving factors such as future population, economy, technological trends, and policies, process-driven IAMs, based on general (partial) equilibrium models or energy system models,[32,50,51] can produce detailed mitigation strategies, mitigation costs, and GHG pathways at various spatial and industrial scales. In contrast, the complexity of cost-benefit IAMs is relatively low, and the representations of the socio-economic and climate systems are relatively simple.[18,32,51] These models are unable to generate detailed climate-related scenarios. They typically measure the total mitigation cost and other economic impacts through highly integrated and simplified indicators.

In contrast, another type of research tool, relying on an increasingly rich data environment, directly employs the climate econometric model to explore the impacts and damages of climate change.[52-54] This type of research captures the relationship between climate and outcomes by parameterizing the impact process; for instance, the temperature-GDP relationship.[54] This type of research can encompass more types of climate impacts and then make up for the deficiencies of past studies; for example, the impacts of climate change on labor productivity, total factor productivity, social conflicts, etc.[55-60]

There is also a certain correlation between the research on IAMs and climate econometrics. Climate econometrics has strengthened the empirical basis for the impact assessment. It can enhance the damage functions in IAMs.[18,61] Conversely, the research based on IAMs can generate scenarios related to climate change, thereby providing scenario input for the climate econometrics model to project future climate risks.[21]

In the subsequent sections, we will combine these two tools to undertake a further review focusing on uncertainty, climate-related scenarios, climate simulations, and climate impacts and damages.

UNCERTAINTIES IN CLIMATE RISK ASSESSMENT

This section initially summarizes several typical uncertainties involved in assessing climate change risks. Subsequent sections will further discuss the related details.

As shown in Table 1, based on the existing literature, we summarize the uncertainty into five types: scenario uncertainty,[62-64] process parameter uncertainty,[11,63,65,66] model uncertainty,[11,21,67] trajectory uncertainty,[68-71] and the uncertainty of decision-makers' risk perception.[72-74] Regarding scenario uncertainty, mitigation (transition) scenarios[62,64,75,76] delineate the potential pathways and trends of future development. This involves socio-economic driving factors such as population, economy, technology, and policies. The establishment of scenarios is predicated on assumptions concerning them. Nevertheless, these assumptions about the future are inherently uncertain,[77] which will ultimately lead to the uncertain pathways of GHG emissions, thereby causing uncertainty in risk projection.[21]

In the transmission chain of climate impacts, uncertainties exist regarding various process parameters. For instance, the climate sensitivity in the process of climate simulation,[78] which reflects the uncertainty of hazards. Also, the estimated coefficients in the climate damage functions, such as those for population deaths[17] and GDP losses[11,21] resulting from temperature rise, reflect the uncertainty of climate vulnerability. Additionally, the social discount rate, which indicates the extent to which the current society pays attention to future social welfare, is employed to discount future climate damage to the present. Nevertheless, there is a significant controversy in its selection[79,80] related to intergenerational equity and the disparities between developed and developing countries.

Model uncertainty arises from the disparities among models in aspects such as structure, parameter configuration, modelling presumptions,

Table 1. Types of uncertainty

Types	Examples	References
Scenario	Mitigation scenario: population, economy, technology, policy, etc	[77]
Process parameter	Climate sensitivity	[78]
	Climate damage parameters	[11,17,21]
	Social discount rate	[79,80]
Model	ESMs/GCMs	[11,17,67]
	Climate impact models	[17]
Trajectory	Simulation in ESMs/GCMs	[68]
	Stochastic IAMs	[71,82]
Decision-makers' risk perception	Attitude towards climate governance → Perception of climate damage → Climate policy	[73,74]

etc.[11,17,67] For simulating future climate change and its impacts, ESMs/GCMs and process-driven climate impact models are frequently employed. Owing to the presence of associated uncertainties, even when the identical emission scenario is inputted, diverse models will produce various climate pathways, leading to uncertainty in the simulation of hazards. The IPCC indicates that currently there is no evidence to demonstrate which model has superior simulation performance;[11] thus, existing studies typically "integrate" the simulation outcomes of multiple models to constitute the model ensembles to reflect the model uncertainty.

Trajectory uncertainty stems from nonlinear dynamic complex systems,[17] such as the climate system and socio-economic system. Such a system is characterized by chaos, namely, seemingly random and irregular motion emerging in a deterministic system, and its behavior is non-repeatable and unpredictable. This kind of system is highly sensitive to the initial value, and when it undergoes a slight change,[68] the output of the system will exhibit significant differences. In the ESMs/GCMs, by changing the initial values of its operation, a series of distinct climate change trajectories, representing such uncertainties, would be generated even if the same input emissions scenario was input. Regarding the socio-economic system, some IAMs incorporate stochastic processes in the socio-economic module and achieve stochastic optimization of the entire model, thereby conducting relevant uncertainty analysis and subsequently characterizing the trajectory uncertainty.

Furthermore, the perception of decision-makers concerning future climate change risks will exert an influence on the formulation of relevant climate policies. This is because the design of climate policies frequently relies on the estimation of climate impacts at the macroeconomic level; however, current research reveals that this estimated value is characterized by significant uncertainty,[19,54] signifying that the decision-making process lacks clear information regarding climate impacts. In light of this, decision-makers holding different political stances on climate change might have diverse perspectives on potential climate risks, which will further result in different policy designs.[73,74]

Overall, the assessment of climate risks encompasses both natural physical and socio-economic processes. It demands cascading the uncertainties involved in all elements throughout the entire transmission chain. Therefore, future research should identify and model the relevant uncertainties in the domains of natural science and social science. Then, they should explore the analytical paradigms and scientific methods that link the elements of uncertainty in different disciplinary fields.[81]

CLIMATE-RELATED SCENARIOS

Climate-related scenarios serve as the foundation for the integrated assessment of climate change risks.[62,83,84] They delineate the evolutionary pathways of the future world in terms of socioeconomics, climate change, and so forth, and each scenario is associated with specific future socio-economic and climate change outcomes. The analysis of climate-related scenarios is not aimed at predicting the future but at simulating various possible states of the future world based on a series of assumptions. According to the climate-related scenarios, decision-makers can understand the associated spatiotemporal characteristics of climate change risks. Climate-related scenarios are mainly categorized into climate scenarios and mitigation (transition) scenarios.

Climate scenarios

Climate scenarios depict the associated climate pathways under specific GHG pathways.[85-87] They delineate the trajectories of climate factors such as radiative forcing, GHG concentrations, temperature, precipitation, and sea level rise. Climate scenarios can be formulated through the simulation outcomes of climate models and climate observation data.

The most commonly utilized climate scenarios are the Representative Concentration Pathways (RCPs), which are designated based on the radiative forcing they attain in 2100.[88] For instance, RCP2.6 and RCP8.5 respectively represent the radiative forcing of 2.6 and 8.5 W/m^2 in 2100. The RCPs encompass the emission and concentration pathways of all GHGs, covering relevant emission sources such as energy systems and land use.[85,86,88]

ESMs/GCMs are complex tools capable of reflecting the interactions among various spheres within the climate system and serve as fundamental tools for constructing climate scenarios. They depict the physical processes of the atmosphere, ocean, cryosphere, and land surface by achieving three-dimensional and high-resolution modelling on a global geographic grid level. For example, BCC-CSM[89], HadCM3,[90] GFDL CM2.X,[91] IGSM,[92,93] MAGICC,[44] FAIR,[94] Hector.[95] A series of ESMs/GCMs emulators with lower resolution and simpler processes are also available for generating scenarios, such as FAIR and MAGICC. Due to their fast running speed, low cost, and ability to simulate the behavior of complex ESMs/GCMs, they are coupled with IAMs to rapidly simulate climate change, thereby offering efficient support for climate risk assessment and climate policy design. Such simplified climate models are widely employed by institutions such as the IPCC.

Mitigation (transition) scenarios

The mitigation (transition) scenarios describe the potential changes made by the socio-economic system to reduce or remove GHG emissions.[83,87] These scenarios depict the trajectories of socio-economic drivers such as the economy, population, technology, and policies over time, and offer mitigation solutions corresponding to these drivers in terms of the economy, energy, land use, etc. Simultaneously, these scenarios also reveal the trajectories of GHG emissions associated with the socio-economic system.

Construction of mitigation (transition) scenarios. The existing studies typically construct scenarios in two ways: Firstly, they are deduced based on one or more constraints such as temperature targets,[96] carbon budgets, or emission pathways; Secondly, they are established in light of the current socio-economic characteristics[76] and the potential future development trends.[62,96]

This section summarizes the construction process of the mitigation (transition) scenarios encompassed in the existing research. As depicted in Figure 3, firstly, determine the qualitative portrayal of the future socio-economic system for this scenario, and formulate quantitative assumptions for the rele-

Table 2. Models for generating scenarios

Categories	Applications	Models	References
Energy System Model	Establish energy transition pathways Design energy policy	MARKAL	[102]
		MESSAGE	[103]
		TIMES	[104]
		PRIMES	[105]
Process-driven IAMs	Establish multi-sectoral mitigation pathways Establish future climate-related scenarios	C^3IAM	[14]
		IMAGE	[48]
		WITCH	[106]
		TIAM	[107]
		MESSAGEix-GLOBIOM	[108]
		AIM	[109]
		GCAM	[47]
		REMIND-MAgPIE	[110]

vant parameters along the dimensions of macroeconomy, technological change, climate policy, and climate targets. The parameters mainly encompass the changes in GDP, population, urbanization rate, technological progress, technological costs, and the timing of implementing mitigation actions, etc.[62,76,83,85,97] Secondly, input the relevant parameters into the economic dynamic module, which encompasses energy, economy, and land use models. It can further generate strategies for alleviating climate change, covering energy consumption and demand, energy mix, low-carbon technology deployment, land use, investment demands for energy transition, and the related pathways of GHGs.[96]

Mitigation (or transition) scenarios are primarily developed using energy system models or IAMs. Table 2 provides an overview of the internationally recognized models used for generating these scenarios, along with their respective applications. As it indicates, the International Energy Agency (IEA) focuses extensively on the global energy transition and predominantly employs energy system models to develop scenarios.[98] These models facilitate the construction of detailed energy transition pathways, including the global and regional energy supply, which encompass clean energy, fossil fuels, energy storage technologies, and negative emission technologies.[99] In contrast, the IPCC adopts a broader perspective by utilizing more complex, process-driven IAMs to generate scenarios. These scenarios address not only the energy system but also other sectors or types, such as agriculture and land-use changes.[38,100] Additionally, these IAMs are capable of constructing macroeconomic transition pathways, including projections related to GDP growth and investment demands.

The IPCC has introduced five Shared Socioeconomic Pathways (SSPs),[76] which serve as quantitative frameworks for describing potential future socioeconomic development trajectories in the absence of climate policy interventions. These pathways are distinguished primarily by their varying levels of challenges related to climate adaptation and mitigation. The SSPs are driven by key parameters such as GDP, population dynamics, and technological progress. By applying different IAMs, the IPCC translates the socioeconomic conditions outlined in the SSPs into specific energy system characteristics, land-use change patterns, and emission pathways. This process generates a set of baseline scenarios that exclude policy interventions.[76]

Furthermore, these IAMs are also utilized to construct scenario matrices. Under the constraint of a specific climate target, the scenario matrices are employed to search for alternative socio-economic pathways to achieve that target[101]. For instance, it is feasible to comprehend the climate mitigation targets that can be attained for each SSP scenario and how these targets correspond to the RCP scenarios. When the climate mitigation targets set by RCPs align with those of SSPs, a set of SSP-RCP combined scenarios can be derived. Each combined scenario reflects a specific socio-economic development pathway, along with the associated information on GHGs and global warming. Based on these scenarios, it is possible to further evaluate the potential climate change risks that the future world will encounter.

Uncertainty of transition scenarios. The uncertainty of climate transition scenarios mainly stems from the driving factors and related models for generating the scenarios. Regarding the driving factors, there is uncertainty in GDP, population, technological progress, etc.[62] The costs of clean technologies like renewable energy and energy storage may be influenced by some uncertain factors,[101] such as shortages of raw materials, the decline in the cost of photovoltaic technology components, and a surge in investment. These factors will make it difficult to predict the cost of clean technologies accurately. At the same time, the learning curve of technological progress cannot be estimated accurately; that is, there is uncertainty in the functional relationship between the cost of clean energy technologies and their cumulative production.[111] Given the two-way feedback effect of "learning by doing" between the deployment and cost of clean technologies,[111] the cost will change uncertainly with technological progress.[77] In addition, factors such as future climate policies and market demands exert an influence on the utilization of clean technologies, and these factors will bring about uncertainty in indicators like the deployment of clean energy or energy mix. Emmerling, et al.[112] discovered that the social discount rate has an impact on the emission pathways and the degree of reliance on carbon removal technologies in the generated scenarios. Currently, there is considerable controversy within the academic community regarding the selection of discount rates, which will also lead to the uncertainty of transition scenarios.

Regarding the models, the process-driven IAMs employed for generating scenarios vary in terms of sub-modules, structures, modelling concepts, and assumptions, and these disparities will also introduce uncertainties. For instance: the MESSAGEix[108] and COFFEE[113] take the energy system model as the core and generate scenarios based on the cost-minimization approach. They do not take into account climate benefits (avoided climate damage). However, process-driven IAMs such as C^3IAM[14] and AIM/CGE[109] do not utilize the cost-minimization method to generate global scenarios. They take computable general (partial) equilibrium models as the core and generate global scenarios by capturing the interaction processes and equilibrium effects among economic sectors. In contrast, IMAGE[48] and GCAM[47] are modelled based on the framework of simulation models rather than optimization models, and they consider climate benefits during the simulation process. Additionally, Daioglou, et al.[114] discovered that there are also differences in the modelling assumptions of future BECCS and CCS in different IAMs, which will further result in uncertainties in the generation of emission pathways.

Risk projection based on climate-related scenarios

The existing studies that project climate change risks based on climate-related scenarios can be generally categorized into five groups (as presented

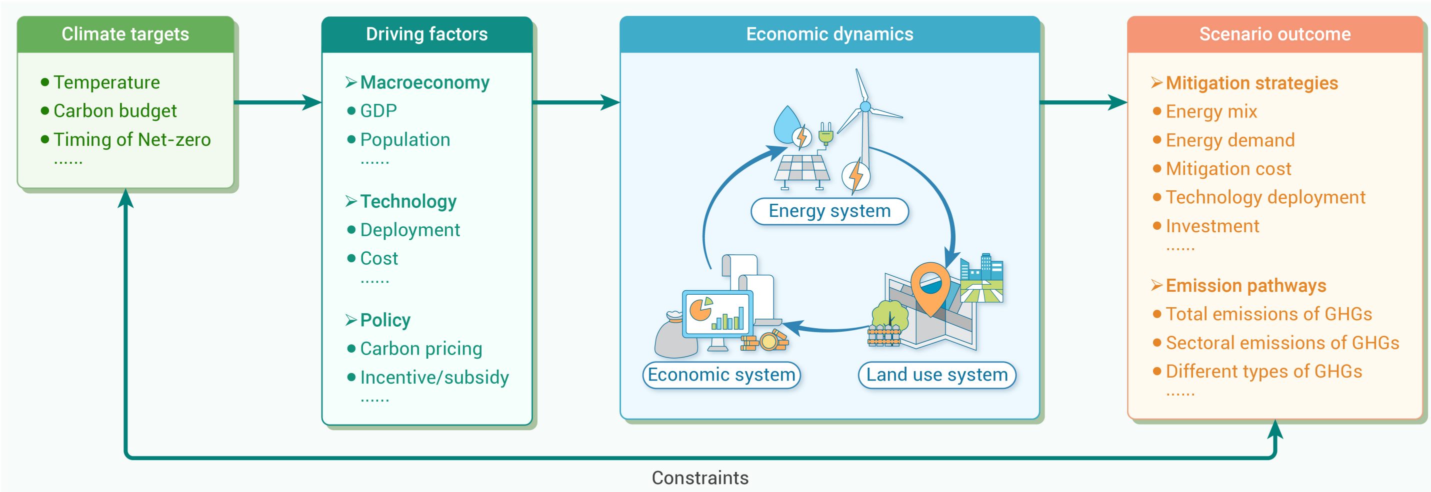


Figure 3. Construction process of climate mitigation scenarios

in Table 3): The first type of studies regards process-driven climate impact models as the mainstay and integrates these models with authoritative climate-related scenarios to project climate risks. For instance: combining the SSP-RCP combination scenarios with process-driven crop models to project yield changes such as those of soybeans, corn, and wheat.[115-117] The second type of research initially constructs a climate econometric model capable of simply characterizing the impacts of climate change. Subsequently, it is combined with climate models and authoritative climate-related scenarios to project risks. For instance: Build the climate econometric models that capture the relationship between global or regional temperatures and GDP,[7,9,11,118] crop yields,[119] energy consumption,[120] etc., to measure vulnerability, and then combine SSP-RCP scenarios to assess climate impacts and damages.

The third type of research centers on cost-benefit IAMs, such as RICE, PAGE, and FUND. This type of research commences from the cost-benefit perspective to identify the optimal climate policy[30,31,35,121] and generate the emission pathways that guarantee the optimal social welfare. Moreover, it projects the economic losses resulting from climate change under the corresponding pathway.[32,73,122] Additionally, some other related studies directly combine cost-benefit IAMs with SSPs to assess the social cost of carbon.[123] Nevertheless, such IAMs are incapable of elaborating on the energy system and other sectors in detail, and it is challenging to establish the relationship between specific mitigation actions and climate change risks.

The fourth type of research focuses on process-driven IAMs. They initially generate climate-related scenarios that can elaborate on the mitigation pathways of economic sectors, energy technologies, and the like. They subsequently assess the climate change risks under the relevant scenarios. For instance, some studies employ models such as GCAM and IMAGE to create decarbonization scenarios that can delineate the transition particulars of the power sector and evaluate the climate impacts and damages related to human health and ecology.[124] Notably, the current research involving process-driven IAMs mainly concentrates on scenario analysis and relatively less on the assessment of climate impacts and damages.[36]

The fifth type of research initially integrates the statistical models or empirical outcomes of climate impact with simplified climate models to establish a novel integrated model framework. Subsequently, it assesses the climate change risks under the corresponding scenarios (including mitigation costs, emission pathways, etc.) generated by process-driven IAMs. Simultaneously, cost-benefit analyses of related scenarios are also conducted. For instance, Drouet et al.[21] selected a series of net-zero transition scenarios produced by mainstream IAMs and input these scenarios into the MAGICC. Then, they combined the climate simulation results with the existing climate damage models to evaluate the climate hazards and the associated risks at the macroeconomic level (GDP loss) under the net-zero transition scenarios. Gambhir et al.[20] adopted a similar modelling approach and evaluated similar characteristics under scenarios spanning 1.5–4 °C temperatures and encompassing a broad range of transition dynamics, that complements and expands on the Network for Greening the Financial System (NGFS) scenarios.

Limitations in the scenarios of IAMs

Simulating the future pathways of low-carbon technologies holds crucial significance in domains such as scenario generation, emission pathway projection, and energy investment planning.[126] Presently, the majority of process-driven IAMs consider "policy" variables as model inputs to generate technology deployment scenarios. As most models are solved through an optimization approach,[126-130] it becomes difficult to identify the corresponding "policy" input (e.g., subsidies or carbon pricing) based on the technology deployment rate desired to simulate. Consequently, it is challenging to fine-tune the deployment rate of energy technologies by directly manipulating the "policy" variable, and thereby it is difficult to freely explore potential energy technology deployment pathways and their impacts on climate change.[126-130] If it is infeasible to generate diverse future climate-related pathways by directly modifying the "technology deployment rate", it might cause policymakers to overlook some potential options for reducing risk.

Additionally, the cost-minimization process in the majority of process-driven IAMs results in the technology deployment rate in each period being affected by the technology cost of the previous period. Conversely, the technology cost in each period is impacted by the technology deployment rate of the previous period. Due to the integration of numerous assumptions and restrictions lacking empirical basis regarding technology deployment and cost in existing related models, the gap between the model settings and the observed values will gradually widen over time within the two-way feedback process of the deployment rate and cost, ultimately causing the technology learning curve in the model to deviate from the empirical findings and be far from reality. When compared with historical observation data, it is found that the mitigation scenarios generated by such models mostly underestimate the deployment rate of key clean technologies[77,126,131] and overestimate the technology cost,[126-130] which may lead policymakers to overlook the options of technology transition with lower costs and their impacts on climate.[101,111]

CLIMATE SIMULATIONS

Models for climate simulation

Climate simulation transforms the emissions produced by the socio-economic system into the relevant physical indicators within the climate system, thereby reflecting the characteristics of climate hazards. From the aspect of model complexity, the climate simulation models utilized for the integrated assessment of climate change risks can be classified into two types: complex ESMs and simplified climate models. Regarding the complex ESMs, they are capable of elaborately depicting the physical processes of the interaction among various systems of the earth. It discretizes the earth's surface into a series of grid areas and can provide climate simulation results with high spatiotemporal resolution. Nevertheless, its running time is excessively long and the running cost is overly high, resulting in low efficiency in conducting simulation studies of climate policies. Even so, driven by the

Table 3. Summary of risk projection based on climate-related scenarios

Types	Cases	References
Process-driven climate impact models + SSPs + RCPs	Combine crop models and SSPs-RCPs to project the yields of soybean and corn	[115,117]
Climate econometrics models + Climate models + SSPs + RCPs	Construct climate econometric models (temperature-GDP/crop yield/energy consumption), and subsequently integrate them with climate models along with RCPs-SSPs to project the climate risks	[9,11,119,120]
Cost-benefit IAMs (scenarios generation + risk assessment)	Generate the optimal mitigation pathway via RICE and then assess the associated climate risks Calculate the social cost of carbon under SSPs through DICE and RICE	[32,73,122,123,125]
Process-driven IAMs (scenarios generation + risk assessment)	Generate the decarbonization scenarios of the power sector through GCAM and PAGE, and then assess the climate risks related to ecosystem and human health under the generated scenarios	[124]
Process-driven IAMs (scenarios generation) + Simplified climate models + Statistical models of climate impacts	Combine a series of net-zero transition scenarios generated by process-driven IAMs with simplified climate models and climate impact statistical models, and evaluate the climate hazards and GDP losses under these scenarios	[21]

demands of natural science research, the majority of studies still rely on a series of ESMs within the Coupled Model Intercomparison Project (CMIP)[132,133] to simulate the climate outcomes under a series of scenarios such as SSPs and RCPs.[133]

However, not all studies related to policy simulation, scenario design, and risk assessment require climate simulation outcomes with high spatiotemporal resolution. Currently, many mainstream IAMs prefer that the climate module be capable of simulating the macroscopic interaction process between the climate system and the socio-economic system at a relatively rapid rate. Consequently, a series of simplified climate models have emerged, such as MAGICC, FAIR, Hector, etc. They retain the fundamental physical conduction mechanism of "emission → concentration → radiative forcing → temperature change" in the climate model and simplify the complex physicochemical processes. Although the simplified models are incapable of fully replicating the interaction behaviors of the complex models, they can take the complex models as the benchmark and simulate the complex models by adjusting their parameters. The existing simplified climate models are primarily employed to simulate the average outcomes of climate change at the global scale, such as the global mean temperature. Additionally, the simplified climate models can also be integrated with the "pattern scaling" models.[71] These models can delineate the statistical relationships between the global mean temperature and the grid temperature in the ESMs,[46,134] thereby facilitating IAMs in rapidly conducting impact assessment studies at a high-resolution spatial scale.

Uncertainties in climate simulation

Climate simulation encompasses process parameter uncertainty, model uncertainty, and trajectory uncertainty. Climate sensitivity is a crucial process parameter,[78] which reflects the changes in global mean temperature when the concentration of carbon dioxide in the atmosphere doubles in comparison to the pre-industrial level. It originates from the uncertainty of internal feedback within the earth system. Existing studies have discovered that the probability density distribution of climate sensitivity peaks approximately at 3°C, and there exists a "long tail" on the right side of the distribution. The Sixth Assessment Report of the IPCC suggests that climate sensitivity is likely to fall within the range of 2.5-4.0°C, with the best estimate being 3°C.[135] Additionally, parameters such as the ocean mixing rate (characterizing the diffusion speed of surface warming in the ocean) and the strength of the climate-carbon cycle feedback (characterizing the degree of regulation of the carbon cycle by the natural system in the context of climate change) are also significant sources of uncertainty in climate simulations. Sampling the distribution functions of these parameters and conducting sensitivity analysis in combination with climate models can characterize the associated uncertainties and thereby depict the risks of climate change.

In addition, diverse ESMs exhibit disparities in structure, parameter configurations, and modelling assumptions, thereby causing model uncertainty. For the identical input emission pathways, distinct ESMs will yield differentiated climate outcomes. Existing studies typically integrate the simulation results of various models in CMIP5 and CMIP6 to signify the model uncertainty.

There is also trajectory uncertainty in climate simulation, which originates from typical nonlinear dynamic complex systems such as the climate system. The climate system possesses chaotic characteristics, namely, seemingly random and irregular movements occur within a deterministic system, and its behavior demonstrates the traits of being non-repeatable and unpredictable. This characteristic renders the simulation of the ESMs extremely sensitive to the initial values. When the initial values of the system undergo minor changes, the output results will present substantial differences. Under the interference of different initial values, the ESMs will generate a series of differentiated climate simulation pathways. To model trajectory uncertainty, distinct climate change trajectories under the same emission scenario can be produced by modifying the initial values of the ESMs.

ASSESSMENT OF IMPACT AND DAMAGE BASED ON IAMS

Damage module

Process-driven IAMs and cost-benefit IAMs not only vary in the resolution of the socio-economic system and the level of detail of scenarios but also exhibit substantial disparities in the climate damage module.[18,19,36,51] Existing literature[18,32,51] suggests that studies modelling the climate damage function are closely related to cost-benefit IAMs. In such models, climate damages are usually modelled by damage functions in relatively simplistic forms. Nevertheless, these damage functions have been established with numerous assumptions by modellers and have thus drawn a series of critiques.[18,54,136] For cost-benefit analysis, they typically measure the climate damage in monetized units. In contrast, although process-driven IAMs can portray detailed biophysical and socio-economic processes, these models have relatively less description of the climate impacts and damages. They attach greater importance to the details of generating scenarios and focus on cost-effectiveness analysis.[17,18,32,51]

Recent trends have demonstrated that a growing number of studies have initiated the incorporation of climate impacts into process-driven IAMs.[18,19,115,137,138] These models have constructed high-resolution climate impact modules in both spatial and process aspects, accurately estimating the effects brought about by climate change, covering multiple regions and sectors. Nevertheless, these studies predominantly focus on the physical-level impacts of climate change rather than the monetized level,[18] such as the reduction in crop yields resulting from global warming,[139] etc.

Compared with cost-benefit IAMs,[51] process-driven IAMs rarely consider the impact of climate change on the macroeconomic system.[32] Recent empirical studies have shown that the impact of climate change on economic growth is cumulative and persistent. Over time, economic losses will accumulate and amplify.[7,140-142] If process-driven IAMs do not feed this impact back to the socio-economic module, it will lead to the generation of biased mitigation scenarios,[137] preventing decision-makers from truly recognizing the severity and urgency of the climate challenges. This gap could also prevent them from understanding the benefits brought about by mitigating climate change and investing in adaptation measures.[143]

In fact, IAMs with general (partial) equilibrium models as the core hold considerable potential in assessing the economic impact of climate change.

These models can elaborate on the transmission mechanism of the impacts of climate change on the socio-economic system in detail and can delineate the interaction effects among economic sectors, providing the net economic impact upon the entire market equilibrium such as the ENVISAGE and GTAP models.[144] They initially evaluate the impact of climate change on factor input and service demand within the economic system through damage functions that measure damages in physical units. Subsequently, the impacts expressed in physical units are input into computable general (partial) equilibrium models to assess the monetized impacts of climate change. Compared with cost-benefit IAMs, process-driven IAMs can more effectively identify the interaction effects among sectors when considering the damage endured by different sectors, thereby reducing the bias in assessing the climate impact at the sectoral or aggregate levels. Therefore, future research should further explore how to incorporate the monetized climate impacts on macroeconomic output into process-driven IAMs.

Limitations in IAMs

Furthermore, there are a series of common limitations for cost-benefit IAMs and process-driven IAMs in modelling climate damages and assessing the associated risks. We summarize them as the following seven points: First, IAMs lack the mechanism for modelling the persistent impact of climate change on economic growth. Based on a series of empirical studies,[54] the estimated disparities in macroeconomic losses mainly stem from the assumptions regarding the persistence of climate impacts, namely, whether climate change affects the economic growth rate (growth effect) or the economic output level (level effect). They show that climate change may reduce economic growth rates persistently, leading to compounding losses. IAMs excluding this effect could severely underestimate cumulative GDP losses over multi-decadal periods. For instance, cumulative losses could differ by several percentage points of global GDP depending on whether growth effects are included[145]. However, many IAMs merely consider level effects. Hence, future research should incorporate the growth effect into IAMs according to the existing empirical findings. Given the current controversy in this aspect,[54] we suggest that future research consider integrating these two impact mechanisms and differentiating the timing of the occurrence of these two mechanisms by modelling the persistence of climate impacts.[54]

Second, the existing IAMs fail to take into account non-market climate damages. Climate change concurrently gives rise to both market losses and non-market losses. Market losses pertain to the losses of goods and services traded in the market. Since their prices are readily observable, these losses can be estimated by the repair or replacement costs of damaged assets. Non-market losses encompass damages that cannot be remedied or reset through market purchasing behaviors, and there are no observable prices available for estimating these losses.[19] For instance, the impact of climate change on health, the destruction of natural assets and ecosystems, and the damage to historical and cultural assets. Current IAMs mainly concentrate on quantifying market losses but are deficient in the assessment and monetization of non-market losses. Incomplete damage assessment will not only impact the accounting of social carbon costs but also influence the assessment of the climate vulnerability of various countries, thereby affecting the decision-making design for adapting to climate change.[146] Hence, it is imperative for future research to further incorporate non-market damages into IAMs.

Thirdly, the current IAMs have inadequate representations of climate adaptation, and the associated modelling overly depends on assumptions.[51] The socio-economic costs of climate change encompass not only the damages resulting from risks but also the adaptation costs expended to adapt to these risks. Meanwhile, future climate adaptation might alter the impact pattern of climate change on the socio-economy. Hence, it is essential for future research to enrich the adjustment effect of adaptation on climate damages and account for the related adaptation costs.

Fourth, to be associated with global climate goals, the climate modules of the majority of IAMs merely simulate the global mean temperature and employ it as the climate hazard for assessing climate damages. In reality, there exist numerous complex mechanisms regarding the impact of climate change on the socio-economic system[18]. For instance, climate change has exerted a differentiated impact on the cooling degree days in diverse regions, thereby bringing about a differentiated impact on the cooling energy demands. Climate change has had a differentiated effect on the accumulated temperature of various regions and different types of crops, leading to differentiated alterations in the yields. Nevertheless, apart from the global mean temperature, few IAMs delineate other climate hazards.[20] Simultaneously, some climate hazards possess distinct regional heterogeneity characteristics, yet few IAMs represent the climate information at the regional level. If regional climate information is lacking and different types of climate hazards are not depicted,[21] it will be arduous to reflect the impact mechanism of climate change and augment the uncertainty in risk assessment. This array of deficiencies will be detrimental to the management of climate change risks in specific regions. However, the simple incorporation of climate and impact models depicting related hazards might significantly enhance the complexity of the model and be disadvantageous for conducting research related to climate policies. Hence, future research is requisite to explore simplified modelling approaches of climate hazards and regional climate information in IAMs.

Fifth, the existing IAMs fall short of depicting the risks engendered by "extreme climate" hazards. The situation where the climate system deviates significantly from its average state is termed "extreme climate", of which climate change will heighten the probability of occurrence.[135] Pendergrass and Hartmann[147] indicated that climate damage might not be proportional to global mean temperature and precipitation. Climate impacts are frequently a function of the extreme values within the distribution of climate factors, and climate damage primarily stems from the shocks of "extreme climate" like heatwaves or floods. For example, models that fail to include extremes may underestimate crop yield losses[148] or infrastructure damages[149] during acute events, leading to risk underestimation, especially in vulnerable regions.[150] Nevertheless, in the current IAMs, the climate damage functions mainly mirror the impacts brought about by the mean state of the climate. If the risks posed by extreme climate are not taken into account, numerous potential climate damages might be overlooked.[17,71,151-153] Hence, future research should incorporate the hazards of extreme climate and their impact processes on the socio-economic system into the climate and impact module of IAMs, such as integrating climate hazards like heat waves and floods and their impacts.

Sixth, a critical limitation lies in the reliance on overly simplified damage functions (e.g., linear, quadratic, exponential forms), particularly in cost-benefit IAMs such as DICE, RICE, FUND, and PAGE. These functions are weakly grounded in empirical results, as evidenced by their failure to incorporate the latest findings from the IAV community.[18] They also fail to capture the complex cross-sectoral and intertemporal propagation of climate impacts. For instance, although estimates of temperature-induced GDP losses exist, many IAMs impose constant elasticities that ignore sector-specific vulnerabilities and adaptive capacity, introducing systematic structural bias into projected damages.[18] Future research should build a stronger bridge between the IAV and mitigation communities, integrating their respective strengths and state-of-the-art advances.

Seventh, in the current studies that employ IAMs for risk assessment, considerations and simulations of uncertainties are relatively scarce. As process-driven IAMs involve a multitude of parameters, large-scale simulations might lead to difficulties in model solving, resulting in a particularly significant deficiency in the quantification of uncertainties of such models. To enhance the simulation efficiency and alleviate the solving challenges, future studies should categorize the key parameters in the socio-economic module and narrow the parameter simulation scope. Concurrently, future studies should also explore rational parameter sampling approaches.[115]

Overall, in the aspect of climate risk assessment, both differences and commonalities exist between cost-benefit IAMs and process-driven IAMs. Future research ought to concurrently enhance these two types of models to promote climate damage modelling. It is worth noting that while addressing their common deficiencies in future research, the integration of the two should also be encouraged to achieve complementary advantages. For instance, some process-driven IAMs with general (partial) equilibrium models as the core can not only reflect the detailed transmission process of climate impacts but also possess the capability to monetize the impacts and damages.[19] Future research can improve the damage function of cost-benefit IAMs based on the assessment results of economic impacts from such models. Furthermore, considering that process-driven IAMs can offer a detailed analysis of mitigation costs, if these models also monetize climate impacts and damages, cost-benefit analysis can also be carried out through them.[21,137] Additionally, against the backdrop of the rapid advancement of artificial intelligence technology, a series of advanced machine learning algorithms based on the "regression" concept have emerged. Future research could integrate relevant algorithms to simplify process-driven climate impact models and establish their emulators, thereby constructing climate damage modules that are simple in form yet capable of restoring the behavior and simulation results of complex process models. Such modules can facilitate the analysis of uncertainties. Such research has gradually emerged, and it has been demonstrated that the gap in simulation performance between simplified models and complex models can be further narrowed.[154,155]

Future research should integrate the merits of the two types of models to attain high-resolution integrated assessment modelling in terms of the transmission process, sectors, technologies, and spatio-temporal scales. This high-resolution modelling would involve multiple dimensions of natural and socio-economic processes, mitigation scenarios, climate change impacts, cost-benefit analysis, climate policies, and uncertainty quantification, which contribute to the conduct of extensive and profound risk management.

ASSESSMENT OF IMPACT AND DAMAGE BASED ON EMPIRICAL MODELS

In risk assessment research where IAMs constitute the main body, modelling climate damage encounters a series of potential challenges and problems. For instance, existing studies have failed to reach a consensus regarding the level effect or growth effect of climate change on economic output, and the persistence of the climate impact remains controversial.[54] These unresolved issues heighten the uncertainty in damage estimation. Additionally, on account of factors such as the deficiency of an empirical basis or the obsolescence of the empirical basis upon which the modelling is founded, the damage functions in the existing IAMs have elicited extensive criticism.[18,136]

In contrast, another form of research, relying on an increasingly rich data environment, directly adopts the climate econometric model as the main entity to investigate the impact of climate change on socio-economic outcomes,[52-54] such as the temperature-GDP relationship.[54] By parameterizing the impact process and establishing reduced-form empirical models, they are capable of covering a greater variety of climate change impacts; for instance, the effects of climate change on labor productivity, total factor productivity, and social conflicts, etc.[55-60] These explorations can compensate for the shortcomings of previous studies. Simultaneously, their empirical results can offer an empirical foundation for constructing the damage function of IAMs; their empirical models can also be directly integrated with complex ESMs and climate-related scenarios to evaluate the risks of climate change. This empirical-based form of research can be categorized as follows: "bottom-up" and "top-down".[19]

'Bottom-up' empirical research

The "bottom-up" research focuses on specific economic sectors, such as energy,[156,157] agriculture,[158,159] industrial production,[160,161] etc.; or specific damage categories, such as migration,[162] social conflicts,[163] labor supply,[164,165] and temperature-related mortality,[166] etc.; or economic factors determining GDP, such as total factor productivity,[59,60] capital,[59] labor.[167] Through the "bottom-up" analytical paradigm, a wider variety of climate impacts can be encompassed. Although the impact of climate change on some sectors or damage categories is not well reflected in GDP, understanding the climate impacts through multiple channels is of great significance for assessing social welfare.

The "bottom-up" approach is capable of summarizing the impacts and damages of climate change from diverse sectors or damage categories. For instance, Hsiang, et al.[168] evaluated the impacts of climate change on agricultural output, mortality rates, electricity, labor, property crimes, and violent crimes in the United States and aggregated these impacts. The findings of this study indicate that under the 1.5°C warming scenario, the total climate damage might be less than 1% of the US GDP. Nevertheless, under the 6°C warming scenario, the total climate damage could exceed 10% of the US GDP. However, when aggregating and accounting for the impacts and damages of climate change through the "bottom-up" approach, the impacts of climate change on certain sectors and damage categories might be overlooked, leading to estimation bias. Additionally, 'bottom-up' aggregation cannot capture the feedback and interaction effects among various sectors; thereby some additional climate change impacts might be omitted.[54]

'Top-down' empirical research

Another type of research is conducted from a "top-down" perspective, directly estimating the impact of climate change on the macroeconomic total output (GDP). In contrast to "bottom-up" research, the merit of this type of research resides in the fact that GDP can directly capture the net effect following interaction and feedback among diverse economic sectors and damage categories. To a certain degree, it circumvents modelling all sectors and damage categories and averts the omission of some potential sectors or damage categories in the "bottom-up" analysis process. Simultaneously, given that the empirical model constructed through a "top-down" approach directly reflects the relationship between temperature and GDP, this research can be directly utilized to enhance the damage function in IAMs.[7,54,61,169,170]

A series of studies have identified robust empirical relationships between regional temperature and regional macroeconomic output.[54,171] These studies encompass research subjects at diverse spatial scales, and the data employed in their empirical analyses also differ in spatial resolution, which involves the scale of countries,[7,118] provinces/states,[9,142] and cities/counties.[172-174]

Besides the disparities in the spatial resolution of the utilized data, these studies also demonstrate variations in the measurement of temperature (employing temperature level or temperature change), functional forms (linear, polynomial, or temperature bin forms), and the specification of interaction and fixed-effect terms in econometric modelling. This series of studies has explored different impact mechanisms and potential characteristics of temperature changes by setting differentiated climate econometric models and functional forms.[54] For example, the non-linear characteristics of climate change impacts, the adaptability of socio-economic systems, the impact of temperature on different sectors, the seasonal impact of temperature, and its impact over different time horizons (near-term, mid-term, and long-term in the 21st century).[54] However, the estimation outcomes of these studies demonstrate considerable uncertainty. Based on the existing results, under the RCP8.5 scenario, the median range of global GDP losses attributed to climate change in 2100 is 7% to 23%.[19] If the uncertainties in the process parameters and the persistence of climate impacts are taken into account, global GDP losses could ascend as high as 90%.[7]

Other limitations and challenges

The "top-down" research also encounters a series of challenges, such as whether climate change will impact economic growth (growth effect) or the level of economic output (level effect) and how long the climate shocks will persist. As depicted in Figure 4, if a temperature shock is imposed at time t, in the level effect model, the temperature rise will merely have a temporary impact on the level of economic output. Once the temperature reverts to the baseline level before the temperature increases, the GDP in the level effect model will also return to the previous baseline pathways. In contrast, the growth effect model assumes that climate change will have a permanent impact on capital and total factor productivity,[169] thereby exerting long-term impacts on the growth of GDP.[7,136,169,175,176] Therefore, in the growth effect model, even if the temperature returns to the baseline level before the temperature rises, the temperature effects on the GDP pathway will not disappear, and the impact might even intensify over time. Take the growth effect model in Figure 4 as an example, we assume that the growth effect exists merely for one unit of time to present the differentiated characteristics of the growth effect and the level effect. Once the macroeconomic system is subjected to the temperature shock at time t, due to the existence of the growth effect, even if the temperature reverts to the baseline temperature at time $t+1$ and the GDP growth rate returns to the baseline value, the evolution trajectory of GDP has changed permanently and the damage cannot be retrieved. However, in contrast to the assumption of "the growth effect of only one unit of time", the growth effect might persist for a longer duration. That is, the impact exerted by the temperature at time t could still have an impact on the GDP at time $t+1$，$t+2$......

Exploring whether temperature shocks cause permanent damage to economic output is essentially an empirical research matter. We propose that future studies construct a set of impulse response curves to depict the impacts brought about by temperature changes over multiple past years. Nevertheless, given the short temporal span of the existing datasets and the considerable noise in related research findings, current studies are unable to clearly determine the duration of persistent temperature shocks. Hence, the duration of temperature shocks on macroeconomic output is also a significant source of uncertainty in climate risk assessment.

To model this uncertainty, persistent assumptions can be adopted in the empirical models (lasting for 1 year, 3 years, 5 years, or 15 years, etc.). Some scholars have modelled the duration of climate shock by the order of the lag term of weather variables by constructing a distributed lag econometric model.[19] Generally, the longer the duration of the climate shocks, the more significant the climate damage. As can be observed from Figure 4, if GDP is impacted by a persistent growth effect, even when the temperature reverts to the baseline temperature, the evolution path of GDP will continue to deviate from the baseline pathway, and the GDP loss will gradually accumulate and magnify over time. Therefore, under the growth effect assumption, the estimated long-term damage from climate change is several orders of magnitude higher than that under the level effect assumption.[7,19,141,177]

Furthermore, existing studies assume that the climate-economic system possesses fundamental stability: namely, the estimated relationship of climate impact based on historical observation data can be extrapolated to project the future. Nevertheless, such extrapolation might disregard some crucial potential climate impacts. On the one hand, considering the nonlinear traits of the climate system, future climate change could trigger climate tipping points with irreversible consequences. For instance, rapid glacier melting. Such climate tipping points might lead to unprecedented systematic changes in natural and human systems.[178] Currently, relevant studies have initiated the assessment of the economic impacts brought about by climate tipping points[178,179] and endeavored to incorporate these impacts into IAMs. On the other hand, unprecedented variations might also arise in the socio-economic system. For example, the emergence of disruptive technologies to address climate change and a considerable enhancement in climate adaptation capabilities, these changes will significantly boost the climate resilience of the socio-economic system. However, current research on adaptation effects mainly centers on individual sectors,[180] and it is challenging to identify climate adaptation effects from a "top-down" perspective.[54,181] Overall, the empirical relationship estimated based on historical observational data is prone to cease being valid for future projection due to the aforementioned two factors, which also introduces uncertainty to the extrapolation and projection of the climate impacts in existing related studies. These manifestations reflect the challenges currently confronted by climate econometric research in differentiating and identifying the effects of short-term weather variations and long-term climate changes. Hence, future studies are required to further explore the impacts of factors such as climate tipping points and climate adaptation[182,183] on economic output.

Some non-market climate impacts are not accounted for in macroeconomic output. For instance, the effects of climate change on human health, migration, ecological species, and so on. Such climate impacts typically involve fewer market processes; thus, future research should focus on how to monetize these impacts. For example, measuring health losses based on the valuation of statistical life (VSL) and accounting for ecological service losses based on the willingness to pay. Furthermore, climate change will further intensify sea-level rise, ocean acidification, and extreme events, and these changes may give rise to a series of cascading climate damages. Currently, "top-down" research seldom encompasses the impacts of such climate hazards on macroeconomic output, and future research should investigate the impact of them on economic output.

Regarding the current research on the socio-economic risk assessment of climate change, the majority of empirical studies focus on the global scale or developed countries and regions, such as the United States and Europe.[172] In contrast, empirical studies concerning developing countries are relatively rare. However, on the one hand, climate hazards demonstrate considerable variations at the global, regional, and national levels. Furthermore, different countries have marked disparities in economic characteristics, governance systems, and development levels, which also exert an influence on their vulnerability and exposure to climate shocks. This gives rise to diverse risk patterns at different spatial scales. On the other hand, the impacts brought about by climate change will spread and diffuse at the regional, national, and even domestic levels. For instance, extreme events may have an impact on the global supply chain and thereby significantly affect global commodity prices,[184,185] which leads to climate change risks being correlated among different spatial scales. Therefore, future related research should incorporate more countries and regions to identify the climate impacts at a more detailed spatial scale, and high-resolution risk assessment studies in developing countries and regions are requisite. This could be conducive to providing detailed risk information and decision support for decision-makers and stakeholders at the global, regional, national, and sub-national levels.

Improvement of the damage module in IAMs

Climate econometrics are capable of providing an empirical basis for improving the damage modules in IAMs. We suggest the following points for improvement: Downscale the global mean temperature simulated by IAMs. The climate econometric models established in existing related studies generally reflect the relationship between regional temperature and regional economic output, while most IAMs only simulate the global mean temperature, lacking consideration of regional information on climate hazards. To match with the findings from climate econometric models,[21,71] we suggest employing the Pattern Scaling technique[134] which exploits the approximately linear relationship between local surface temperature and global mean temperature, while taking into account the spatio-temporal auto-correlated random noise,[71] to achieve regional downscaling.

Combine the climate econometric model with ESMs/GCMs. The climate econometric model is capable of assessing the related climate impacts based on the high-resolution temperature variations simulated by ESMs/GCMs at the spatiotemporal level. Subsequently, it combines the impact results with the climate outcomes in ESMs/GCMs to establish the statistical relationship between the global mean temperature and the associated climate impacts at the regional, local, or grid level.[180]

Endogenously model the growth effect of climate change on macroeconomic output. The impact of climate change on capital stock and total factor productivity is the main cause for the persistent climate effect. Modellers can integrate the existing empirical findings and endogenously establish the relationship between temperature and capital stock or total factor productivity in the economic module of IAMs.[54]

Meta-analysis. In the domain of IAV, a considerable number of studies have been carried out based on observable historical data and employing state-of-the-art statistical techniques to evaluate the impact and damage of climate change. We suggest modellers should integrate the outcomes of diverse empirical studies within IAV and calibrate the relevant parameters of the damage function through meta-analysis.

SUMMARY AND FUTURE PERSPECTIVES

Climate-related scenarios, climate simulation, climate impact and damage, as well as uncertainty, constitute the key elements of the integrated assessment of climate change. We summarize the evidence from the domains of Mitigation and IAV, and incorporate those four critical elements into the IPCC's risk framework, thereby providing a systematic understanding of assessing climate change risks at the socio-economic level. We identified that the tools for risk assessment mainly include IAMs and climate econometric models. Both process-driven IAMs and cost-benefit IAMs are available for generating emission pathways of GHGs and computing the associated mitigation costs. Process-driven IAMs provide detailed process and analysis of energy systems, economic sectors, land use, and climate impacts, which is suitable for generating detailed climate-related scenarios. While cost-benefit IAMs are simpler in model complexity and measure the total mitigation cost and other economic impacts through highly integrated and simplified indicators. In contrast to IAMs, climate econometric models, which use historical data to establish reduced-form relationships between climate and outcomes, are capable of covering a wider range of impacts than IAMs. There is also a correlation between the two kinds of tools, as climate econometric models can improve IAM damage functions, and IAM scenarios can inform climate econometric models for risk projections.

As for uncertainty, five types are identified including scenario uncertainty, process parameter uncertainty, model uncertainty, trajectory uncertainty, and uncertainty in decision-makers' risk perception. Existing evidence implies that IAMs currently underrepresent these uncertainties and suggests that future research should aim to identify and model these uncertainties across natural and social sciences, as well as explore methods to connect the uncertainties across different disciplines.

Climate-related scenarios are essential and the construction of mitigation scenarios is approached in two distinct manners: either by inferring from predefined constraints, such as temperature targets and carbon budgets, or by reflecting on the current socio-economic landscape and anticipated development trajectories. The choice of models is contingent upon the scope of analysis, with energy system models being employed to address global energy transition scenarios, and the more sophisticated IAMs being used for a comprehensive sectoral analysis. It is noteworthy that climate and mitigation scenarios are not mutually exclusive, and IAMs are capable of producing integrated scenarios that encompass both. The assessment of climate risk is inherently fraught with uncertainties in scenarios, which arise from a multitude of driving factors, including GDP, population, technological advancement, and social discount rates, as well as from model-specific disparities in scenario generation techniques, the valuation of climate benefits, and the modelling assumptions related to BECCS and CCS.

The research on risk projections through the application of climate-related scenarios can also be identified and categorized into five aspects. First, process-driven climate impact models are integrated with authoritative climate scenarios to project risks. Second, climate econometric models are developed to characterize climate impacts and combined with climate models and scenarios for risk projection. Third, cost-benefit IAMs are utilized to identify optimal climate policies, generate emission pathways, and project economic losses. Fourth, process-driven IAMs generate detailed scenarios by themselves and assess risks associated with them. Finally, statistical models or empirical climate impact data are integrated with simplified climate models to create new frameworks for risk assessment under scenarios generated by process-driven IAMs, including cost-benefit analyses.

Additionally, a critical limitation we identified in scenario generation within process-driven IAMs primarily stems from the reliance on policy inputs and optimization methods, which hinder the precise calibration of deployment rates and overlook potential pathways. The incorporation of numerous assumptions and constraints without empirical support exacerbates errors in the process of cost optimization, impeding the accurate depiction of technology learning curves and leading to underestimations of clean technology deployment and overestimations of costs. Future studies are urged to refine energy system modelling to mitigate these constraints.

In terms of climate simulation, the selection of climate models is determined by the specific requirements and objectives of climate simulation. Complex ESMs and GCMs are suited for research demanding high precision and resolution, albeit at the cost of computational speed and efficiency. While simplified models are preferred for rapid simulation and assessment. Existing simplified models predominantly simulate global-scale climate change outcomes, such as global mean temperature. However, to enhance resolution, we suggest that these models can further be integrated with the "pattern scaling" approach, enabling IAMs to conduct high-resolution impact assessments efficiently. Climate simulation encompasses uncertainties related to process parameters, model structure, and trajectories, which can be characterized and assessed through parameter sampling, sensitivity analysis, model ensembles, and perturbation of initial conditions.

Climate damage plays a core role in assessing risks. In cost-benefit IAMs, climate damages are modelled using simplistic damage functions focusing on monetized damage. However, they have been criticized for their numerous underlying assumptions and lack of empirical basis. Process-driven IAMs, while detailed in biophysical and socio-economic processes, offer less insight into damage quantification and prioritize scenario generation and cost-effectiveness analysis. A recent trend involves integrating high-resolution climate impact modules into process-driven IAMs, yet these studies mainly address physical impacts rather than monetized damages. These models can better capture sectoral interactions, thereby reducing biases in economic impact assessments. To enhance the accuracy of assessments, future research should aim to integrate monetized climate impacts into process-driven IAMs.

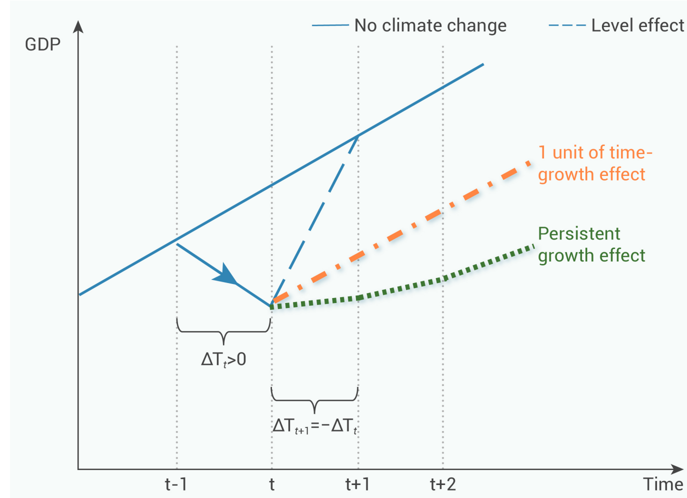


Figure 4. The persistence of the climate impacts on GDP. It is assumed that the impact of temperature on GDP remains identical in both the level effect and growth effect within the same period.[148]

We also reveal several pervasive limitations of damages within IAMs. Firstly, IAMs do not adequately model the cumulative and persistent effects of climate on economic growth, which have been frequently identified in empirical research. This could skew mitigation scenario generation. Secondly, they overlook non-market climate damages. Thirdly, IAMs have insufficient representations of climate adaptation, with modelling heavily reliant on assumptions. Fourthly, IAMs predominantly simulate global mean temperature as a proxy for climate hazards, which may not capture localized hazards and their impacts. Fifthly, IAMs underrepresent the risks associated with extreme climate events. Sixthly, there is a disconnect between IAM research and the field of IAV, with IAMs not incorporating recent empirical findings from IAV.

In conclusion, future research directions for enhancing the damage modules within IAMs suggest to synthesize the strengths of both IAM types to develop high-resolution IAMs that encompass a broad spectrum of natural and socio-economic processes, mitigation strategies, climate impacts, economic analyses, policy evaluations, and uncertainty assessments, thereby advancing the field of climate risk management.

Empirical research is also of importance for modelling damages, which can be divided into "bottom-up" and "top-down". "Bottom-up" research, which focuses on specific sectors or damage categories, provides a more diverse assessment of climate impacts than IAMs but may omit feedback and interaction effects due to aggregation issues. Conversely, "top-down" modelling encompasses all sectors in the market, preventing omissions and can directly enhance IAM damage functions. Studies have identified robust relationships between regional temperature and macroeconomic output across various spatial scales, using different temperature metrics, functional forms, and econometric specifications. These studies explore the impact mechanisms and characteristics of temperature changes, including the persistent temperature shocks and long-run climate effects. Future research should develop impulse response curves to depict the persistent effects of temperature changes, although current datasets' limitations and research noise impede clear determinations of persistent shock durations. Current empirical studies also lack consideration of climate adaptation, non-market impacts, and climate tipping points, affecting the extrapolation of empirical models for risk projections and necessitating attention in future research. Given the regional and national diffusion of climate impacts and the scarcity of empirical studies in developing countries, future research should expand to more countries and regions for detailed spatial-scale climate impact identification and high-resolution risk assessments, particularly in developing areas.

To enhance the damage module of IAMs, future research should integrate climate econometric models, ESMs/GCMs, and IAMs through statistical downscaling to achieve scale matching. Additionally, empirical findings on climate shocks can be leveraged to refine the impact mechanisms within process-driven IAMs, thereby endogenously modelling the persistence of climate shocks on economic growth. In addition, in the domain of IAV, a multitude of studies have been conducted using historical data and state-of-the-art statistical methods to assess climate impacts. It is recommended that modellers synthesize the findings from these diverse empirical studies and calibrate the damage function parameters via meta-analysis.

REFERENCES

1. Rezaei E.E. and Gohar L. (2023). Climate change impacts on crop yields. *Nat. Rev. Earth Environ.* **4**:831–846. DOI:10.1038/s43017-023-00491-0
2. Pryor S.C., Barthelmie R.J., Bukovsky M.S., et al. (2020). Climate change impacts on wind power generation. *Nat. Rev. Earth Environ.* **1**:627–643. DOI:10.1038/s43017-020-0101-7
3. Zhang Z., Hui H. and Song Y. (2025). Mitigating the vicious cycle between urban heatwaves and building energy systems in Guangdong–Hong Kong–Macao Greater Bay Area. *Innov. Energy* **2**:100080. DOI:10.59717/j.xinn-energy.2025.100080
4. Matthews T., Wilby R.L., Kala C.P., et al. (2025). Mortality impacts of the most extreme heat events. *Nat. Rev. Earth Environ.* **6**:193–210. DOI:10.1038/s43017-024-00635-w
5. Adshead D., Fuldauer L.I., Thacker S., et al. (2024). Climate threats to coastal infrastructure and sustainable development outcomes. *Nat. Clim. Chang.* **14**:344–352. DOI:10.1038/s41558-024-01950-2
6. Cheng Y., Li C., Xu Y., et al. (2024). Extreme impacts on electric power systems from non-catastrophic meteorological conditions. *Innov. Energy* **1**:100008. DOI:10.59717/j.xinn-energy.2024.100008
7. Burke M., Hsiang S.M. and Miguel E. (2015). Global non-linear effect of temperature on economic production. *Nature* **527**:235–239. DOI:10.1038/nature15725
8. Tran T.-N.-D., Tapas M.R., Do S.K., et al. (2024). Investigating the impacts of climate change on hydroclimatic extremes in the Tar-Pamlico River basin, North Carolina. *J. Environ. Manage.* **363**:121375. DOI:10.1016/j.jenvman.2024.121375
9. Chang J.J., Wei Y.M., Yuan X.C., et al. (2020). The Nonlinear Impacts of Global Warming on Regional Economic Production: An Empirical Analysis from China. *Weather Clim. Soc.* **12**:759–769. DOI:10.1175/WCAS-D-20-0029.1
10. Tran T.-N.-D. and Lakshmi V. (2024). Enhancing human resilience against climate change: Assessment of hydroclimatic extremes and sea level rise impacts on the Eastern Shore of Virginia, United States. *Sci. Total Environ.* **947**:174289. DOI:10.1016/j.scitotenv.2024.174289
11. Burke M., Davis W.M. and Diffenbaugh N.S. (2018). Large potential reduction in economic damages under UN mitigation targets. *Nature* **557**:549–553. DOI:10.1038/s41586-018-0071-9
12. Marshall S.R.O., Tran T.-N.-D., Arshad A., et al. (2025). SWAT and CMIP6-driven hydro-climate modeling of future flood risks and vegetation dynamics in the White Oak Bayou Watershed, United States. *Earth Syst. Environ.* DOI:10.1007/s41748-025-00621-2.
13. Wei Y.M., Han R., Liang Q.M., et al. (2020). Self-preservation strategy for approaching global warming targets in the post-Paris Agreement era. *Nat. Commun.* **11**:1624. DOI:10.1038/s41467-020-15453-z
14. Wei Y.M., Han R., Wang C., et al. (2018). An integrated assessment of INDCs under Shared Socioeconomic Pathways: an implementation of C3IAM. *Nat. Hazards* **92**:585–618. DOI:10.1007/s11069-018-3297-9
15. Wei Y.-M., Kang J.-N. and Chen W. (2022). Climate or Carbon Mitigation Engineering Management. *Engineering* **17**:17–21. DOI:10.1016/j.eng.2021.09.008
16. Intergovernmental Panel on Climate Change. (2023). Climate Change 2022: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge University Press).
17. Rising J., Tedesco M., Piontek F., et al. (2022). The missing risks of climate change. *Nature* **610**:643–651. DOI:10.1038/s41586-022-05243-6
18. Diaz D. and Moore F. (2017). Quantifying the economic risks of climate change. *Nat. Clim. Chang.* **7**:774–782. DOI:10.1038/NCLIMATE3411
19. Piontek F., Drouet L., Emmerling J., et al. (2021). Integrated perspective on translating biophysical to economic impacts of climate change. *Nat. Clim. Chang.* **11**:563–572. DOI:10.1038/s41558-021-01065-y
20. Gambhir A., Butnar I., Li P.H., et al. (2022). Near-term transition and longer-term physical climate risks of greenhouse gas emissions pathways. *Nat. Clim. Chang.* **12**:88–96. DOI:10.1038/s41558-021-01236-x
21. Drouet L., Bosetti V., Padoan S.A., et al. (2021). Net zero-emission pathways reduce the physical and economic risks of climate change. *Nat. Clim. Chang.* **11**:1070–1076. DOI:10.1038/s41558-021-01218-z
22. Tapas M.R., Tran T.-N.-D., Do S.K., et al. (2024). A methodological framework for assessing sea level rise impacts on nitrate loading in coastal agricultural watersheds using SWAT+: A case study of the Tar-Pamlico River basin, North Carolina, USA. *Sci. Total Environ.* **951**:175523. DOI:10.1016/j.scitotenv.2024.175523
23. Nguyen B.Q., Van Binh D., Tran T.-N.-D., et al. (2024). Response of streamflow and sediment variability to cascade dam development and climate change in the Sai Gon Dong Nai River basin. *Clim. Dyn.* **62**:7997–8017. DOI:10.1007/s00382-024-07319-7
24. Tran T.N.D., Nguyen B.Q., Grodzka-Łukaszewska M., et al. (2024). Investigating the Future Flood and Drought Shifts in the Transboundary Srepok River Basin Using CMIP6 Projections. *IEEE JSTAEORS* **17**:7516–7529. DOI:10.1109/JSTARS.2024.3380514
25. Schwoerer T., Ives M.C., Knowlton J.G., et al. (2023). Climate policy must account for community-specific socio-economic, health, and biophysical conditions—evidence from coastal Alaska. *Reg. Environ. Change* **23**:90. DOI:10.1007/s10113-023-02080-9
26. Reinwald F., Thiel S., Kainz A., et al. (2024). Components of urban climate analyses for the development of planning recommendation maps. *Urban Clim.* **57**:102090. DOI:10.1016/j.uclim.2024.102090
27. Tran T.-N.-D., Nguyen B.Q., Grodzka-Łukaszewska M., et al. (2023). The role of reservoirs under the impacts of climate change on the Srepok River basin, Central Highlands of Vietnam. *Front. Environ. Sci.* **11**:1304845. DOI:10.3389/fenvs.2023.1304845
28. Intergovernmental Panel on Climate Change. (2014). Climate Change 2014 – Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects: Working Group II Contribution to the IPCC Fifth Assessment Report (Cambridge University Press).
29. Liu H., Mi Z., Wu M., et al. (2024). The Innovation Energy: An international journal of energyscience and engineering. *Innov. Energy* **1**:100001. DOI:10.59717/j.xinn-energy.2024.100001
30. Nordhaus W.D. (1993). Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. *Resour. Energy Econ.* **15**:27–50. DOI:10.1016/0928-7655(93)90017-O
31. Tol R.S.J. and Fankhauser S. (1998). On the representation of impact in integrated assessment models of climate change. *Environ. Model. Assess.* **3**:63–74. DOI:10.1023/a:1019050503531
32. Wilson C., Guivarch C., Kriegler E., et al. (2021). Evaluating process-based integrated assessment models of climate change mitigation. *Clim. Change* **166**:1–22. DOI:10.1007/s10584-021-03099-9
33. Batten S. (2018). Climate change and the macro-economy: a critical review. *Bank of England Working Papers* :706. DOI:10.2139/ssrn.3104554.
34. Nordhaus W.D. (2017). Evolution of Assessments of the Economics of Global Warming Changes in the DICE model, 1992 – 2017. *Natl. Bur. Econ. Res. Work. Pap. Ser.* :23319. DOI:10.3386/w23319.
35. Weyant J. (2017). Some Contributions of Integrated Assessment Models of Global Climate. *Change. Rev. Environ. Econ. Policy* **11**:115–137. DOI:10.1093/reep/rew018
36. Bosetti V. (2021). Integrated Assessment Models for Climate Change. *Oxford Res. Encycl. Econ. Fin.* DOI:10.1093/acrefore/9780190625979.013.572.
37. Nordhaus W.D. (2017). Revisiting the social cost of carbon. *PNAS* **114**:1518–1523. DOI:10.1073/pnas.1609244114
38. Silva Herran D., Tachiiri K. and Matsumoto K.i. (2019). Global energy system transformations in mitigation scenarios considering climate uncertainties. *Appl. Energy* **243**:119–131. DOI:10.1016/j.apenergy.2019.03.069
39. Luderer G., Madeddu S., Merfort L., et al. (2022). Impact of declining renewable energy costs on electrification in low-emission scenarios (vol 7, pg 32, 2022). *Nat. Energy* **7**:380–381. DOI:10.1038/s41560-022-01000-1
40. Johns T.C., Durman C.F., Banks H.T., et al. (2006). The new Hadley Centre Climate Model (HadGEM1): Evaluation of coupled simulations. *J. Clim.* **19**:1327–1353. DOI:10.1175/JCLI3712.1
41. Castruccio S., McInerney D.J., Stein M.L., et al. (2014). Statistical Emulation of Climate Model Projections Based on Precomputed GCM Runs. *J. Clim.* **27**:1829–1844. DOI:10.1175/JCLI-D-13-00099.1
42. van Vuuren D.P., Edmonds J., Kainuma M., et al. (2011). How well do integrated assessment models simulate climate change. *Clim. Change* **104**:255–285. DOI:10.1007/s10584-009-9764-2
43. Tebaldi C., Armbruster A., Engler H.P., et al. (2020). Emulating climate extreme indices. *Environ. Res. Lett.* **15**:074006. DOI:10.1088/1748-9326/ab8332
44. Meinshausen M., Raper S.C.B. and Wigley T.M.L. (2011). Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6–Part 1: Model description and calibration. *Atmos. Chem. Phys.* **11**:1417–1456. DOI:10.5194/acp-11-1417-2011
45. Millar R.J., Nicholls Z.R., Friedlingstein P., et al. (2017). A modified impulse-response representation of the global near-surface air temperature and atmospheric concentration response to carbon dioxide emissions. *Atmos. Chem. Phys.* **17**:7213–7228. DOI:10.5194/acp-17-7213-2017
46. Yuan X.C., Zhang N., Wang W.Z., et al. (2021). Large-scale emulation of spatio-temporal variation in temperature under climate change. *Environ. Res. Lett.*

16:014041. DOI:10.1088/1748-9326/abd213
47. Calvin K., Patel P., Clarke L., et al. (2019). GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. Geosci. *Model Dev.* 12:677–698. DOI:10.5194/gmd-12-677-2019.
48. Stehfest E., van Vuuren D., Bouwman L., et al. (2014). Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications. (Netherlands Environmental Assessment Agency (PBL)).
49. Manne A.S. and Richels R.G. (2005). MERGE: an integrated assessment model for global climate change. *Energy Environ.*:175–189.
50. Farmer J.D., Hepburn C., Mealy P., et al. (2015). A Third Wave in the Economics of Climate Change. *Environ. Resour. Econ.* 62:329–357. DOI:10.1007/s10640-015-9965-2
51. Rising J.A., Taylor C., Ives M.C., et al. (2022). Challenges and innovations in the economic evaluation of the risks of climate change. *Ecol. Econ.* 197:107437. DOI:10.1016/j.ecolecon.2022.107437
52. Hsiang S. (2016). Climate Econometrics. *Annu. Rev. Resour. Econ.* 8:43–75. DOI:10.1146/annurev-resource-100815-095343
53. Castle J.L. and Hendry D.F. (2022). Econometrics for Modelling Climate Change. *Oxford Res. Encycl. Econ. Fin.* DOI:10.1093/acrefore/9780190625979.013.675.
54. Chang J.J., Mi Z.F. and Wei Y.M. (2023). Temperature and GDP: A review of climate econometrics analysis. *Struct. Chang. Econ. Dyn.* 66:383–392. DOI:10.1016/j.strueco.2023.05.009
55. Fankhauser S. and Tol R.S.J. (2005). On climate change and economic growth. *Resour. Energy Econ.* 27:1–17. DOI:10.1016/j.reseneeco.2004.03.003
56. Lecocq F. and Shalizi Z. (2007). How might climate change affect economic growth in developing countries? A review of the growth literature with a climate lens. *World Bank Policy Res. Work. Pap.* :4315.
57. Graff Zivin J. and Neidell M. (2009). Medical technology adoption, uncertainty, and irreversibilities: is a bird in the hand really worth more than in the bush. *Health Econ.* 19:142–153. DOI:10.1002/hec.1455
58. Zhang P., Deschenes O., Meng K., et al. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *J. Environ. Econ. Manage.* 88:1–17. DOI:10.1016/j.jeem.2017.11.001
59. Henseler M. and Schumacher I. (2019). The impact of weather on economic growth and its production factors. *Clim. Change* 154:417–433. DOI:10.1007/s10584-019-02441-6
60. Letta M. and Tol R.S.J. (2019). Weather, Climate and Total Factor Productivity. *Environ. Resour. Econ.* 73:283–305. DOI:10.1007/s10640-018-0262-8
61. Moore F.C. and Diaz D.B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Chang.* 5:127–131. DOI:10.1038/nclimate2481
62. Gambhir A., Ganguly G. and Mittal S. (2022). Climate change mitigation scenario databases should incorporate more non-IAM pathways. *Joule* 6:2663–2667. DOI:10.1016/j.joule.2022.11.007
63. Drouet L., Bosetti V. and Tavoni M. (2015). Selection of climate policies under the uncertainties in the Fifth Assessment Report of the IPCC. *Nat. Clim. Chang.* 5:937–940. DOI:10.1038/NCLIMATE2721
64. van Vuuren D.P., Kriegler E., O'Neill B.C., et al. (2014). A new scenario framework for climate change research: scenario matrix architecture. *Clim. Change* 122:373–386. DOI:10.1007/s10584-013-0906-1
65. Burke M., Dykema J., Lobell D.B., et al. (2015). Incorporating Climate Uncertainty into Estimates of Climate Change Impacts. *Rev. Econ. Stat.* 97:461–471. DOI:10.1162/REST_a_00478
66. Kunreuther H., Heal G., Allen M., et al. (2013). Risk management and climate change. *Nat. Clim. Chang.* 3:447–450. DOI:10.1038/NCLIMATE1740
67. Frigg R., Bradley S., Du H., et al. (2014). Laplace's demon and the adventures of his apprentices. *Philos. Sci.* 81:31–59. DOI:10.1086/674416
68. Stainforth D.A., Allen M.R., Tredger E.R., et al. (2007). Confidence, uncertainty and decision-support relevance in climate predictions. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* 365:2145–2161. DOI:10.1098/rsta.2007.2074
69. Daron J.D. and Stainforth D.A. (2013). On predicting climate under climate change. *Environ. Res. Lett.* 8:034021. DOI:10.1088/1748-9326/8/3/034021
70. Hawkins E., Smith R.S., Gregory J.M., et al. (2016). Irreducible uncertainty in near-term climate projections. *Clim. Dyn.* 46:3807–3819. DOI:10.1007/s00382-015-2806-8
71. Kikstra J.S., Waidelich P., Rising J., et al. (2021). The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. *Environ. Res. Lett.* 16:094037. DOI:10.1088/1748-9326/ac1d0b
72. Hornsey M.J., Harris E.A., Bain P.G., et al. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nat. Clim. Chang.* 6:622–626. DOI:10.1038/NCLIMATE2943
73. Yang P., Mi Z., Yao M., et al. (2021). The impact of climate risk valuation on the regional mitigation strategies. *J. Clean. Prod.* 313:127786. DOI:10.1016/j.jclepro.2021.127786
74. Kousser T. and Tranter B. (2018). The influence of political leaders on climate change attitudes. *Glob. Environ. Change* 50:100–109. DOI:10.1016/j.gloenvcha.2018.03.005
75. O'Neill B.C., Tebaldi C., van Vuuren D.P., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* 9:3461–3482. DOI:10.5194/gmd-9-3461-2016
76. Riahi K., van Vuuren D.P., Kriegler E., et al. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Glob. Environ. Change* 42:153–168. DOI:10.1016/j.gloenvcha.2016.05.009
77. Jaxa-Rozen M. and Trutnevyte E. (2021). Sources of uncertainty in long-term global scenarios of solar photovoltaic technology. *Nat. Clim. Chang.* 11:266–273. DOI:10.1038/s41558-021-00998-8
78. Forster P.M., Maycock A.C., McKenna C.M., et al. (2020). Latest climate models confirm need for urgent mitigation. *Nat. Clim. Chang.* 10:7–10. DOI:10.1038/s41558-019-0660-0
79. Nordhaus W. (2019). Climate Change: The Ultimate Challenge for Economics. *Am. Econ. Rev.* 109:1991–2014. DOI:10.1257/aer.109.6.1991
80. Hänsel M.C., Drupp M.A., Johansson D.J.A., et al. (2020). Climate economics support for the UN climate targets. *Nat. Clim. Chang.* 10:781–789. DOI:10.1038/s41558-020-0833-x
81. Burke M., Hsiang S.M. and Miguel E. (2016). Climate Economics. *Science* 352:292–293. DOI:10.1126/science.aad9634
82. Calel R., Chapman S.C., Stainforth D.A., et al. (2020). Temperature variability implies greater economic damages from climate change. *Nat. Commun.* 11:5028. DOI:10.1038/s41467-020-18797-8
83. O'Neill B.C., Carter T.R., Ebi K.L., et al. (2020). Achievements and needs for the climate change scenario framework. *Nat. Clim. Chang.* 10:1074–1084. DOI:10.1038/s41558-020-00952-0
84. Sutton R.T. (2019). Climate Science Needs to Take Risk Assessment Much More Seriously. *Bull. Am. Meteorol. Soc.* 100:1637–1642. DOI:10.1175/BAMS-D-18-0280.1
85. Moss R.H., Edmonds J.A., Hibbard K.A., et al. (2010). The next generation of scenarios for climate change research and assessment. *Nature* 463:747–756. DOI:10.1038/nature08823
86. Lamarque J.F., Bond T.C., Eyring V., et al. (2011). Global and regional evolution of short-lived radiatively-active gases and aerosols in the Representative Concentration Pathways. *Clim. Change* 109:191–212. DOI:10.1007/s10584-011-0155-0
87. Rosentrater L.D. (2010). Representing and using scenarios for responding to climate change. *Wiley Interdiscip. Rev. Clim. Change* 1:253–259. DOI:10.1002/wcc.32
88. van Vuuren D.P., Edmonds J., Kainuma M., et al. (2011). The representative concentration pathways: an overview. *Clim. Change* 109:5–31. DOI:10.1007/s10584-011-0148-z
89. Wu T.W., Lu Y.X., Fang Y.J., et al. (2019). The Beijing Climate Center Climate System Model (BCC-CSM): the main progress from CMIP5 to CMIP6. *Geosci. Model Dev.* 12:1573–1600. DOI:10.5194/gmd-12-1573-2019
90. Hassan W.H. and Nile B.K. (2021). Climate change and predicting future temperature in Iraq using CanESM2 and HadCM3 modeling. *Model. Earth Syst. Environ.* 7:737–748. DOI:10.1007/s40808-020-01034-y
91. Chapman C.C., Monselesan D.P., Risbey J.S., et al. (2022). A large-scale view of marine heatwaves revealed by archetype analysis. *Nat. Commun.* 13:7843. DOI:10.1038/s41467-022-35493-x
92. Paltsev S. and Sokolov A. (2021). Scenarios with MIT Integrated Global Systems Model: Significant Global Warming Regardless of Different Approaches. *World Sci. Encycl. Clim. Change Case Stud. Clim. Risk Action Oppor.* 2:235–241. DOI:10.1007/s10584-009-9792-y
93. Sokolov A.P., Schlosser C.A., Dutkiewicz S., et al. (2005). MIT integrated global system model (IGSM) version 2: model description and baseline evaluation. (MIT Joint Program on the Science and Policy of Global Change).
94. Smith C.J., Forster P.M., Allen M., et al. (2018). FAIR v1.3: a simple emissions-based impulse response and carbon cycle model. *Geosci. Model Dev.* 11:2273–2297. DOI:10.5194/gmd-11-2273-2018.
95. Hartin C.A., Patel P., Schwarber A., et al. (2015). A simple object-oriented and open-source model for scientific and policy analyses of the global climate system–Hector v1.0. *Geosci. Model Dev.* 8:939–955. DOI:10.5194/gmd-8-939-2015.
96. Rogelj J., Popp A., Calvin K.V., et al. (2018). Scenarios towards limiting global mean temperature increase below 1.5 °C. *Nat. Clim. Chang.* 8:325–332. DOI:10.1038/s41558-018-0091-3.
97. Lee J.Y., Marotzke J., Bala G., et al. (2023). Future Global Climate: Scenario-Based Projections and Near-Term Information. Masson-Delmotte V., Zhai P., Pirani A., et al. (eds). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge University Press), pp:553–672. DOI:10.1017/9781009157896.006.
98. Brecha R.J., Ganti G., Gidden M.J., et al. (2022). Institutional decarbonization scenarios evaluated against the Paris Agreement 1.5 °C goal. *Nat. Commun.* 13:4304. DOI:10.1038/s41467-022-31734-1.
99. Kober T., Schiffer H.-W., Densing M., et al. (2020). Global energy perspectives to 2060–WEC's World Energy Scenarios 2019. *Energy Strategy Rev.* 31:100523. DOI:10.1016/j.esr.2020.100523
100. Grubler A., Wilson C., Bento N., et al. (2018). A low energy demand scenario for meeting the 1.5°C target and sustainable development goals without negative

emission technologies. *Nat. Energy* 3:515–527. DOI:10.1038/s41560-018-0172-6.
101. Ives M., Mercure J.-F., Way R., et al. (2021). A new perspective on decarbonising the global energy system. (Smith School of Enterprise and the Environment, University of Oxford), Report No. 21-04.
102. Zonooz M.R.F., Nopiah Z., Yusof A.M., et al. (2009). A review of MARKAL energy modeling. *Eur. J. Sci. Res.* 26:352–361.
103. Pfenninger S., Hawkes A. and Keirstead J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renew. Sustain. Energy Rev.* 33:74–86. DOI:10.1016/j.rser.2014.02.003
104. Loulou R. and Labriet M. (2008). ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure. *Comput. Manag. Sci.* 5:7–40. DOI:10.1007/s10287-007-0046-z
105. Mantzos L. (2009). Overview of primes energy system model. (E3MLab of National Technical University of Athens).
106. Bosello F. and Cian E.D. (2014). Documentation on the development of damage functions and adaptation in the WITCH model. *CMCC Res. Pap.* :RP0228.
107. Gracceva F. and Zeniewski P. (2013). Exploring the uncertainty around potential shale gas development–A global energy system analysis based on TIAM (TIMES Integrated Assessment Model). *Energy* 57:443–457. DOI:10.1016/j.energy.2013.06.006
108. Guo F., van Ruijven B., Zakeri B., et al. (2021). Global Energy Interconnection: A scenario analysis based on the MESSAGEix-GLOBIOM Model. (International Institute for Applied Systems Analysis).
109. Fujimori S., Hasegawa T. and Masui T. (2017). AIM/CGE V2.0: Basic Feature of the Model. Fujimori S., Kainuma M. and Masui T. (eds). Post-2020 Climate Action: Global and Asian Perspectives (Springer Singapore):281–302. DOI:10.1007/978-981-10-3869-3_13.
110. Hilaire J. and Bertram C. (2020). The REMIND-MAgPIE model and scenarios for transition risk analysis. (Potsdam Institute for Climate Impact Research).
111. Way R., Ives M.C., Mealy P., et al. (2022). Empirically grounded technology forecasts and the energy transition. *Joule* 6:2057–2082. DOI:10.1016/j.joule.2022.08.009
112. Emmerling J., Drouet L., van der Wijst K.I., et al. (2019). The role of the discount rate for emission pathways and negative emissions. *Environ. Res. Lett.* 14:104008. DOI:10.1088/1748-9326/ab3cc9
113. de Oliveira C.C., Angelkorte G., Rochedo P.R., et al. (2021). The role of biomaterials for the energy transition from the lens of a national integrated assessment model. *Clim. Change* 167:57. DOI:10.1007/s10584-021-03201-1
114. Daioglou V., Rose S.K., Bauer N., et al. (2020). Bioenergy technologies in long-run climate change mitigation: results from the EMF-33 study. *Clim. Change* 163:1603–1620. DOI:10.1007/s10584-020-02799-y
115. Moore F.C., Baldos U., Hertel T., et al. (2017). New science of climate change impacts on agriculture implies higher social cost of carbon. *Nat. Commun.* 8:1607. DOI:10.1038/s41467-017-01792-x
116. Jägermeyr J., Müller C., Ruane A.C., et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nat. Food* 2:873–885. DOI:10.1038/s43016-021-00400-y
117. Heinicke S., Frieler K.A., Jägermeyr J., et al. (2022). Global gridded crop models underestimate yield responses to droughts and heatwaves. *Environ. Res. Lett.* 17:044026. DOI:10.1088/1748-9326/ac592e
118. Kahn M.E., Mohaddes K., Ng R.N., et al. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Econ.* 104:105624. DOI:10.1016/j.eneco.2021.105624
119. Rising J. and Devineni N. (2020). Crop switching reduces agricultural losses from climate change in the United States by half under RCP 8.5. *Nat. Commun.* 11:4991. DOI:10.1038/s41467-020-18725-w.
120. Rode A., Carleton T., Delgado M., et al. (2021). Estimating a social cost of carbon for global energy consumption. *Nature* 598:308–314. DOI:10.1038/s41586-021-03883-8
121. Nordhaus W.D. (1992). An Optimal Transition Path for Controlling Greenhouse Gases. *Science* 258:1315–1319. DOI:10.1126/science.258.5086.1315
122. Cai Y.Y. and Lontzek T.S. (2019). The Social Cost of Carbon with Economic and Climate Risks. *J. Polit. Econ.* 127:2684–2734. DOI:10.1086/701890
123. Yang P., Yao Y.F., Mi Z., et al. (2018). Social cost of carbon under shared socioeconomic pathways. *Glob. Environ. Change* 53:225–232. DOI:10.1016/j.gloenvcha.2018.10.001
124. Luderer G., Pehl M., Arvesen A., et al. (2019). Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. *Nat. Commun.* 10:5229. DOI:10.1038/s41467-019-13067-8
125. Ricke K., Drouet L., Caldeira K., et al. (2018). Country-level social cost of carbon. *Nat. Clim. Chang.* 8:895–900. DOI:10.1038/s41558-018-0282-y
126. Creutzig F., Agoston P., Goldschmidt J.C., et al. (2017). The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* 2:17140. DOI:10.1038/nenergy.2017.140
127. Xiao M., Junne T., Haas J., et al. (2021). Plummeting costs of renewables - Are energy scenarios lagging. *Energy Strategy Rev.* 35:100636. DOI:10.1016/j.esr.2021.100636
128. Hoekstra A., Steinbuch M. and Verbong G. (2017). Creating Agent-Based Energy Transition Management Models That Can Uncover Profitable Pathways to Climate Change Mitigation. *Complexity* 2017:1967645. DOI:10.1155/2017/1967645
129. Shiraki H. and Sugiyama M. (2020). Back to the basic: toward improvement of technoeconomic representation in integrated assessment models. *Clim. Change* 162:13–24. DOI:10.1007/s10584-020-02731-4
130. Victoria M., Haegel N., Peters I.M., et al. (2021). Solar photovoltaics is ready to power a sustainable future. *Joule* 5:1041–1056. DOI:10.1016/j.joule.2021.03.005
131. Wilson C., Grubler A., Bauer N., et al. (2012). Future capacity growth of energy technologies: are scenarios consistent with historical evidence. *Clim. Change* 118:381–395. DOI:10.1007/s10584-012-0618-y
132. Huntingford C., Williamson M.S. and Nijsse F.J.M.M. (2020). CMIP6 climate models imply high committed warming. *Clim. Change* 162:1515–1520. DOI:10.1007/s10584-020-02849-5
133. Tebaldi C., Debeire K., Eyring V., et al. (2020). Climate model projections from the scenario model intercomparison project (ScenarioMIP) of CMIP6. *Earth Syst. Dyn. Discuss.* 2020:1–50. DOI:10.5194/esd-2020-68
134. Herger N., Sanderson B.M. and Knutti R. (2015). Improved pattern scaling approaches for the use in climate impact studies. *Geophys. Res. Lett.* 42:3486–3494. DOI:10.1002/2015GL063569
135. Masson-Delmotte V., Zhai P., Pirani A., et al. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge University Press).
136. Pindyck R.S. (2013). Climate change policy: what do the models tell us. *J. Econ. Lit.* 51:860–872. DOI:10.1257/jel.51.3.860
137. Schultes A., Piontek F., Rogelj J., et al. (2021). Economic damages from on-going climate change imply deeper near-term emission cuts. *Environ. Res. Lett.* 16:104053. DOI:10.1088/1748-9326/ac27ce
138. Takakura J.Y., Takahashi K., Fujimori S., et al. (2019). Dependence of economic impacts of climate change on anthropogenically directed pathways. *Nat. Clim. Chang.* 9:737–741. DOI:10.1038/s41558-019-0578-6
139. Snyder A., Calvin K., Phillips M., et al. (2020). The domestic and international implications of future climate for US agriculture in GCAM. *PLoS ONE* 15:e0237918. DOI:10.1371/journal.pone.0237918
140. Carleton T.A. and Hsiang S.M. (2016). Social and economic impacts of climate. *Science* 353:aad9837. DOI:10.1126/science.aad9837
141. Dell M., Jones B.F. and Olken B.A. (2014). What do we learn from the weather. *The new climate-economy literature. J. Econ. Lit.* 52:740–798. DOI:10.1257/jel.52.3.740
142. Kalkuhl M. and Wenz L. (2020). The impact of climate conditions on economic production. *Evidence from a global panel of regions. J. Environ. Econ. Manage.* 103:102360. DOI:10.1016/j.jeem.2020.102360
143. Pindyck R.S. (2017). The Use and Misuse of Models for Climate Policy. *Rev. Environ. Econ. Policy* 11:100–114. DOI:10.1093/reep/rew012
144. Roson R. and Sartori M. (2016). Estimation of Climate Change Damage Functions for 140 Regions in the GTAP 9 Database. *J. Glob. Econ. Anal.* 1:78–115. DOI:10.21642/JGEA.010202AF
145. Howard P.H. and Sterner T. (2025). Methodology Matters: A Careful Meta-Analysis of Climate Damages. *Environ. Resour. Econ.* DOI:10.1007/s10640-025-01016-7.
146. Islam M.M. (2022). Distributive justice in global climate finance – Recipients' climate vulnerability and the allocation of climate funds. *Glob. Environ. Change* 73:102475. DOI:10.1016/j.gloenvcha.2022.102475
147. Pendergrass A.G. and Hartmann D.L. (2014). The Atmospheric Energy Constraint on Global-Mean Precipitation Change. *J. Clim.* 27:757–768. DOI:10.1175/JCLI-D-13-00163.1
148. Lesk C., Rowhani P. and Ramankutty N. (2016). Influence of extreme weather disasters on global crop production. *Nature* 529:84–87. DOI:10.1038/nature16467
149. Forzieri G., Bianchi A., e Silva F.B., et al. (2018). Escalating impacts of climate extremes on critical infrastructures in Europe. *Glob. Environ. Change* 48:97–107. DOI:10.1016/j.gloenvcha.2017.11.007
150. Byers E., Gidden M., Leclère D., et al. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environ. Res. Lett.* 13:055012. DOI:10.1088/1748-9326/aabf45
151. DeFries R.S., Edenhofer O., Halliday A., et al. (2019). The missing economic risks in assessments of climate change impacts. (Grantham Research Institute on Climate Change and the Environment, The Earth Institute at Columbia University, Potsdam Institute for Climate Impact Research).
152. Carleton T. and Greenstone M. (2022). A guide to updating the US Government's social cost of carbon. *Rev. Environ. Econ. Policy* 16:196–218. DOI:10.1086/720988
153. Stern N., Stiglitz J., Karlsson K., et al. (2022). A Social Cost of Carbon Consistent with a Net-Zero Climate Goal. (Roosevelt Institute).
154. Sarofim M.C., Waldhoff S.T. and Anenberg S.C. (2021). A temperature binning approach for multi-sector climate impact analysis. *Clim. Change* 165:22. DOI:10.1007/s10584-021-03048-6
155. Takakura J., Fujimori S., Hanasaki N., et al. (2021). Reproducing complex simulations of economic impacts of climate change with lower-cost emulators. *Geosci. Model Dev.* 14:3121–3140. DOI:10.5194/gmd-14-3121-2021
156. Auffhammer M. and Mansur E.T. (2014). Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Econ.* 46:522–530. DOI:10.1016/j.eneco.2014.04.017

157. Davis L.W. and Gertler P.J. (2015). Contribution of air conditioning adoption to future energy use under global warming. *PNAS* **112**:5962–5967. DOI:10.1073/pnas.1423558112
158. Schlenker W. and Roberts M.J. (2009). Nonlinear temperature effects indicate severe damages to U. *S. crop yields under climate change. PNAS* **106**:15594–15598. DOI:10.1073/pnas.0906865106
159. Schlenker W., Michael Hanemann W. and Fisher A.C. (2005). Will US agriculture really benefit from global warming. *Accounting for irrigation in the hedonic approach. Am. Econ. Rev.* **95**:395–406. DOI:10.1257/0002828053828455
160. Hsiang S.M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *PNAS* **107**:15367–15372. DOI:10.1073/pnas.1009510107
161. Chen X.G. and Yang L. (2019). Temperature and industrial output: Firm-level evidence from China. *J. Environ. Econ. Manage.* **95**:257–274. DOI:10.1016/j.jeem.2017.07.009
162. Missirian A. and Schlenker W. (2017). Asylum applications respond to temperature fluctuations. *Science* **358**:1610–1613. DOI:10.1126/science.aao0432
163. Carleton T., Hsiang S.M. and Burke M. (2016). Conflict in a changing climate. *Eur. Phys. J. Spec. Top.* **225**:489–511. DOI:10.1140/epjst/e2015-50100-5
164. Dasgupta S., van Maanen N., Gosling S.N., et al. (2021). Effects of climate change on combined labour productivity and supply: an empirical, multi-model study. *Lancet Planet. Health* **5**:e455–e465. DOI:10.1016/S2542-5196(21)00170-4
165. Neidell M., Graff Zivin J. and Sheahan M. (2021). Temperature and work: Time allocated to work under varying climate and labor market conditions. *PLoS ONE* **16**:e0254224. DOI:10.1371/journal.pone.0254224
166. Yang J., Yin P., Zhou M., et al. (2021). Projecting heat-related excess mortality under climate change scenarios in China. *Nat. Commun.* **12**:1039. DOI:10.1038/s41467-021-21305-1
167. Graff Zivin J. and Neidell M. (2014). Temperature and the allocation of time: Implications for climate change. *J. Labor Econ.* **32**:1–26. DOI:10.1086/671766
168. Hsiang S., Kopp R., Jina A., et al. (2017). Estimating economic damage from climate change in the United States. *Science* **356**:1362–1368. DOI:10.1126/science.aal4369
169. Dell M., Jones B.F. and Olken B.A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *Am. Econ. J. Macroecon.* **4**:66–95. DOI:10.1257/mac.4.3.66
170. Lemoine D. and Kapnick S. (2016). A top-down approach to projecting market impacts of climate change. *Nat. Clim. Chang.* **6**:51–55. DOI:10.1038/NCLIMATE2759
171. Newell R.G., Prest B.C. and Sexton S.E. (2021). The GDP-Temperature relationship: Implications for climate change damages. *J. Environ. Econ. Manage.* **108**:102445. DOI:10.1016/j.jeem.2021.102445
172. Burke M. and Tanutama V. (2019). Climatic constraints on aggregate economic output. *Natl. Bur. Econ. Res. Work. Pap.* :25779. DOI:10.3386/w25779.
173. Colacito R., Hoffmann B. and Phan T. (2019). Temperature and Growth: A Panel Analysis of the United States. *J. Money Credit Bank.* **51**:313–368. DOI:10.1111/jmcb.12574
174. Yuan X.C., Yang Z.M., Wei Y.M., et al. (2020). The Economic Impacts of Global Warming on Chinese Cities. *Clim. Change Econ.* **11**:2050007. DOI:10.1142/S2010007820500074
175. Stern N. (2013). The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models. *J. Econ. Lit.* **51**:838–859. DOI:10.1257/jel.51.3.838
176. Hsiang S.M. and Jina A.S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. *Natl. Bur. Econ. Res. Work. Pap.* :20352. DOI:10.3386/w20352.
177. Pretis F., Schwarz M., Tang K., et al. (2018). Uncertain impacts on economic growth when stabilizing global temperatures at 1.5°C or 2°C warming. Philos. Trans. *R. Soc. A Math. Phys. Eng. Sci.* **376**:20160460. DOI:10.1098/rsta.2016.0460.
178. Dietz S., Rising J., Stoerk T., et al. (2021). Economic impacts of tipping points in the climate system. *PNAS* **118**:e2103081118. DOI:10.1073/pnas.2103081118
179. Cai Y., Judd K.L., Lenton T.M., et al. (2015). Environmental tipping points significantly affect the cost-benefit assessment of climate policies. *PNAS* **112**:4606–4611. DOI:10.1073/pnas.1503890112
180. Carleton T., Jina A., Delgado M., et al. (2022). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits. *Q. J. Econ.* **137**:2037–2105. DOI:10.1093/qje/qjac020
181. Auffhammer M. (2018). Quantifying Economic Damages from Climate Change. *J. Econ. Perspect.* **32**:33–52. DOI:10.1257/jep.32.4.33
182. Burke M. and Emerick K. (2016). Adaptation to Climate Change: Evidence from US Agriculture. *Am. Econ. J. Econ. Policy* **8**:106–140. DOI:10.1257/pol.20130025
183. Chapagain D., Baarsch F., Schaeffer M., et al. (2020). Climate change adaptation costs in developing countries: insights from existing estimates. *Clim. Dev.* **12**:934–942. DOI:10.1080/17565529.2020.1711698
184. Malik A., Li M., Lenzen M., et al. (2022). Impacts of climate change and extreme weather on food supply chains cascade across sectors and regions in Australia. *Nat. Food* **3**:631–643. DOI:10.1038/s43016-022-00570-3
185. Lau C.K., Cai Y. and Gozgor G. (2023). How do weather risks in Canada and the United States affect global commodity prices? Implications for the decarbonisation process. *Ann. Oper. Res.* DOI:10.1007/s10479-023-05672-0.

FUNDING AND ACKNOWLEDGMENTS

The authors are grateful for financial support from the National Natural Science Foundation of China (NSFC) (Grant Nos.72293605, 72488101, 72404025, 72074021), the China Postdoctoral Science Foundation (CPSF) (Grant Nos.2024M754101, 2025T181113), the Postdoctoral Fellowship Program of CPSF (Grant No.GZC20242169), and the Social Science Foundation of Beijing, China (Grant No. 25BJ03021). We also thank all colleagues from the Center for Energy & Environmental Policy Research, Beijing Institute of Technology (CEEP-BIT).

AUTHOR CONTRIBUTIONS

Y.-M. Wei and Z. Mi supervised the research activities, designed the study, and reviewed and edited the manuscript. J.-J. Chang conceptualized the study, wrote the original draft, performed the analysis, prepared visualizations and compiled the paper. B. Yu and X.-C. Yuan performed analysis and edited the manuscript. B. Yang, S.-Y. Liu, and Y.-X. Hu collected and analysed the literature. All authors discussed the content and contributed to the writing of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND MATERIALS AVAILABILITY

Data are available from the corresponding author upon reasonable request.