

COMPASS: a comprehensive Climate-gOvernance Modeling & Policy ASsessment System supporting cutting-edge climate research

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Received: 26 January 2026; Revised: 12 May 2026; Accepted: 10 June 2026

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ABSTRACT

This paper introduces a comprehensive Climate-gOvernance Modeling & Policy ASsessment System (COMPASS) developed by the School of Ecology & Environment, Renmin University of China. The COMPASS includes a top-down computable general equilibrium model (CE3-CGE), a bottom-up energy technology model (PECE), a localized integrated assessment model (GCAM-CHN), as well as econometric and machine learning approaches. Together, these models simulate multi-scale interactions across energy systems, technological details, and macroeconomic dynamics, supporting policy analysis ranging from macrostructural trends to micro-level technoeconomic features, and from long-term pathways to short-term fluctuations. The COMPASS could provide robust scientific support for China's carbon neutrality governance and contribute methodological advances and scenario-based insights to the broader field of global climate policy research.

KEYWORDS

Climate-gOvernance Modeling & Policy ASsessment System (COMPASS), computable general equilibrium, energy technology model, integrated assessment model, econometric and machine learning.

1 Introduction

Addressing climate change and promoting sustainable development involve complex interactions among social economy, energy technologies, environmental feedbacks, policy instruments, and multiple other dimensions. For instance, carbon pricing not only impacts the structure of energy production and consumption but also transmits through industrial chains to affect macroeconomic performance and social welfare, while generating long-term feedbacks on environmental and resource systems; and energy technology innovation and industrial upgrading reshape economic structures and carbon emission pathways, intensifying the interplay among energy, economic, and environmental systems. Against this backdrop, clarifying cross-system linkages to provide scientific support for policy formulation, industrial planning, and investment decisions requires multi-level and multi-dimensional modeling tools. The development and application of such models represent not merely a central focus of international academia, but a cornerstone of global climate governance and policy design. In particular, the assessment reports of the Intergovernmental Panel on Climate Change^[1,2] have relied heavily on modeling tools represented by integrated assessment models (IAMs), computable general equilibrium (CGE) models, and energy technology models, whose scenario simulations have provided core quantitative evidence for informing global mitigation pathways, energy transition strategies, and technology deployment roadmaps.

However, a single model often struggles to fully capture the complex interactions across broad systems. To meet the increasingly comprehensive research needs in the future, developing an integrated framework that incorporates representative models holds significant academic and practical value. The School of Ecology & Environment, Renmin University

of China has developed a systematic Climate-gOvernance Modeling & Policy ASsessment System (COMPASS), as shown in Figure 1, which includes its independently constructed CGE model and a bottom-up energy technology model, a localized IAM, as well as econometric and machine learning models. Similar to most CGE models, China Energy-Environment-Economy Recursive Dynamic CGE Model (CE3-CGE) captures macroeconomic dynamics, inter-sectoral resource flows, and policy shock effects, enabling assessments of the socio-economic impacts of carbon pricing, subsidies, and various fiscal and tax policies. The technology-driven Programme of Energy and Climate Economics (PECE) simulates the costs, efficiencies, market penetration, and deployment potential of various energy technologies under different scenarios, providing guidance for energy transition pathways and technology choices. The China-localized Global Change Analysis Model (GCAM-CHN), as an IAM, integrates the energy system with land, climate, and water systems, allowing for long-term, cross-regional, and cross-sectoral scenario simulations for climate mitigation, energy transition, and sustainable development. Econometric and machine learning models, on the other hand, conduct refined analysis, interpretation, and forecasting of economic fluctuations, price dynamics, and market responses, providing empirical evidence for understanding policy effectiveness and economic phenomena. By including these complementary models, the COMPASS balances technical granularity and economic consistency, enabling comprehensive simulation and interpretation ranging from macroeconomic trends to micro-level technologies, and from long-term scenarios to short-term fluctuations.

As one of the world's largest carbon-emitting countries, China faces the significant challenge of achieving carbon neutrality before 2060 while balancing economic growth with ecological conservation. The COMPASS integrates internationally advanced

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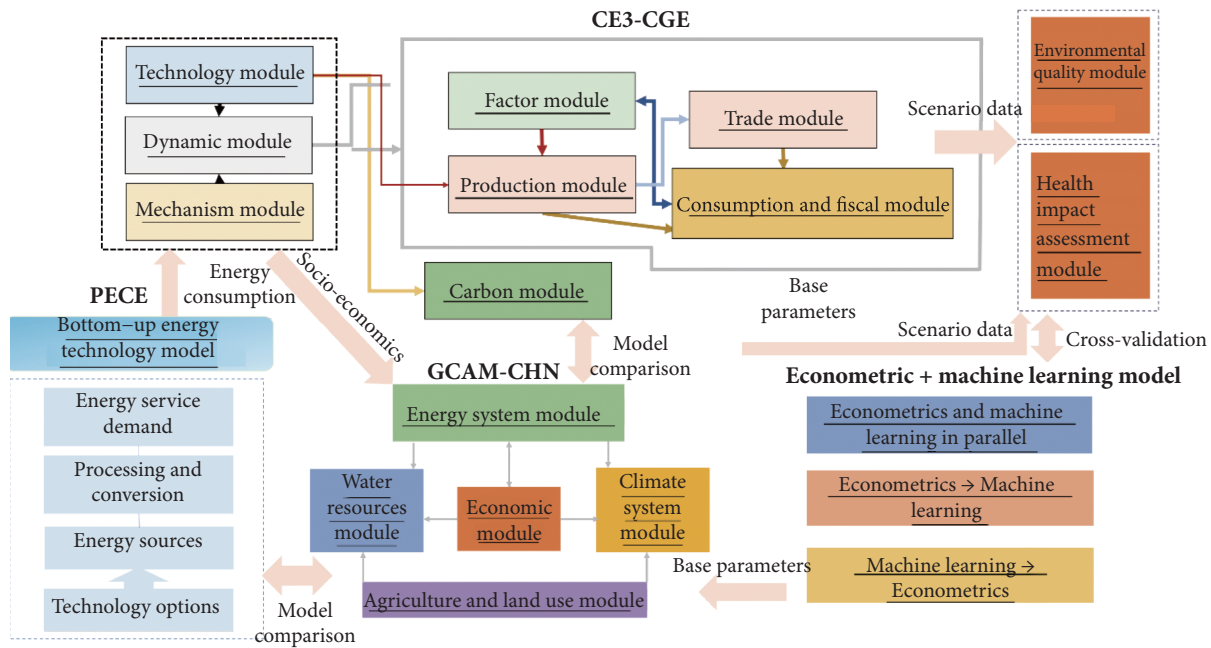


Fig. 1 Overview of the Climate-gOvernance Modeling &Policy ASsessment System (COMPASS) hosted by School of Ecology & Environment, Renmin University of China. More details can be found in [Figure A1](#).

methodologies in energy and climate economics. By combining analyses from energy, environment, and economic perspectives, it enables quantitative assessment of the multi-faceted effects of mitigation policies, energy strategies, technology choices, and market mechanisms. The COMPASS is therefore expected to provide scenario-based evidence for designing China's carbon neutrality pathways and offer methodological contributions for global climate and energy research.

2 Modeling methodologies

This section will introduce the principles, characteristics, and modeling details of the CE3-CGE, PECE, GCAM-CHN, and econometric and machine learning models included in the COMPASS.

2.1 CE3-CGE model

To capture the macroeconomic implications of energy and climate policies, the COMPASS incorporates the CE3-CGE model within a general equilibrium framework. The CE3-CGE framework offers an integrated platform for evaluating the economic, energy, and environmental effects of policy measures related to taxation, trade, energy transition, and climate change mitigation. As a top-down model, it provides a consistent representation of economy-wide interactions and serves as the macroeconomic foundation of the COMPASS.

2.1.1 Overview

The CE3-CGE (China Energy-Environment-Economy Computable General Equilibrium) model is developed within a standard CGE framework, extended to incorporate detailed energy structures, environmental linkages, and dynamic features for long-term pathway simulations. The model consists of two versions: the national single-region model (CE3-CNCGE) and the multi-regional model (CE3-MRCGE)^[8]. The former captures aggregate policy impacts at the national scale, while the latter provides province-level differentiation across China's 31 regional

economies (The Hong Kong Special Administrative Region, the Macao Special Administrative Region, and Taiwan province are not included due to data availability).

1) Temporal and sectoral coverage. The base year of the CE3-CGE model is 2020, with calibration to the latest national and provincial input-output tables and energy balance data published by the National Bureau of Statistics^[4,5]. The model distinguishes 42 production sectors, covering primary, industrial, service, and energy-related activities. A comprehensive Social Accounting Matrix (SAM) was constructed to ensure internal consistency between production, income, and expenditure flows among institutions, factors, and commodities.

2) Spatial framework. The national model provides a macro-level representation of the Chinese economy, while the multi-regional version captures spatial heterogeneity in production structure, resource endowment, and energy mix across 31 provinces. Inter-regional trade is endogenously determined within the multi-regional system, allowing the identification of cross-regional spillover effects of energy and climate policies.

3) Dynamic mechanism. The CE3-CGE operates under a recursive dynamic structure, in which capital accumulation, labor force evolution, and total factor productivity (TFP) growth are updated exogenously between periods^[6]. This design enables the simulation of long-term economic and emission trajectories under alternative policy, technology, and demographic assumptions.

2.1.2 Structural features

The CE3-CGE model adopts a multi-tier nested constant elasticity of substitution (CES) production structure, with enhanced representation of the energy system and negative emission technologies. Compared with conventional CGE frameworks, it integrates multiple energy carriers and detailed abatement options into a unified analytical system, linking economic activity with physical energy flows and emission processes. In particular, the model explicitly incorporates carbon capture and storage (CCS), bioenergy with CCS (BECCS), direct air capture with CCS

(DACCS), and nature-based carbon sinks, each formulated as independent production activities with technology-specific cost structures and substitution elasticities. This design allows for process-based assessment of low-carbon and negative-emission pathways, rather than relying on aggregated abatement functions.

1) Detailed representation of energy use. Energy commodities are fully disaggregated into coal, oil, natural gas, electricity, heat, and renewable energy. Within electricity generation, the model distinguishes between fossil-based (coal-, oil-, and gas-fired) and renewable-based (wind, solar photovoltaic, hydropower, nuclear, and biomass) technologies, each characterized by unique input combinations, substitution elasticities, and emission coefficients. This fine resolution enables simulation of the structural evolution of China's energy mix under different policy and technology scenarios.

2) Integration of low-carbon and negative-emission technologies. The technology module forms an important innovation of the CE3-CGE system. It explicitly represents both low-carbon options—such as CCS retrofitted to fossil plants, electrification, and energy efficiency improvements—and negative-emission technologies including BECCS, DACCS, and nature-based sinks. Each is modeled through a nested CES structure linking intermediate inputs, capital–labor composites, and energy factors. Varying substitution elasticities across nests capture differences in technological flexibility and cost dynamics over time.

3) Illustrative nested structure and analytical flexibility. Taking CCS technology as an example, a nested CES function is used to represent the capacity of this technology, as shown in Eq. (1), where A_{CCS} denotes the scale parameter, INT denotes intermediate inputs, α denotes the share parameter, and $\sigma = 1/(1 - \rho)$ denotes the elasticity of substitution. KL denotes the capital (K)–labor (L) composite endowment factor, which is itself a CES aggregation of capital and labor, as calculated in Eq. (2). The parameters of these formulae, differentiated by subscript, correspond directly to their counterparts in the CES function for CCS technology. Furthermore, labor is further decomposed into high-skilled labor (L_H) and low-skilled labor (L_L), as shown in Eq. (3).

$$CCS = A_{CCS} [\alpha KL^\rho + (1 - \alpha) INT^\rho]^{1/\rho} \quad (1)$$

$$KL = A_{KL} [\alpha_{KL} K^{\rho_{KL}} + (1 - \alpha_{KL}) L^{\rho_{KL}}]^{1/\rho_{KL}} \quad (2)$$

$$L = A_L [\alpha_L L_H^{\rho_L} + (1 - \alpha_L) L_L^{\rho_L}]^{1/\rho_L} \quad (3)$$

This nested structure, as shown in Figure 2, provides flexibility through different elasticities of substitution. This hierarchical nesting provides analytical flexibility to represent technological, factor, and labor heterogeneity. Similar formulations are applied to other energy and mitigation technologies, ensuring internal consistency across the model system. Through this integrated structure, the CE3-CGE model captures the interactions between

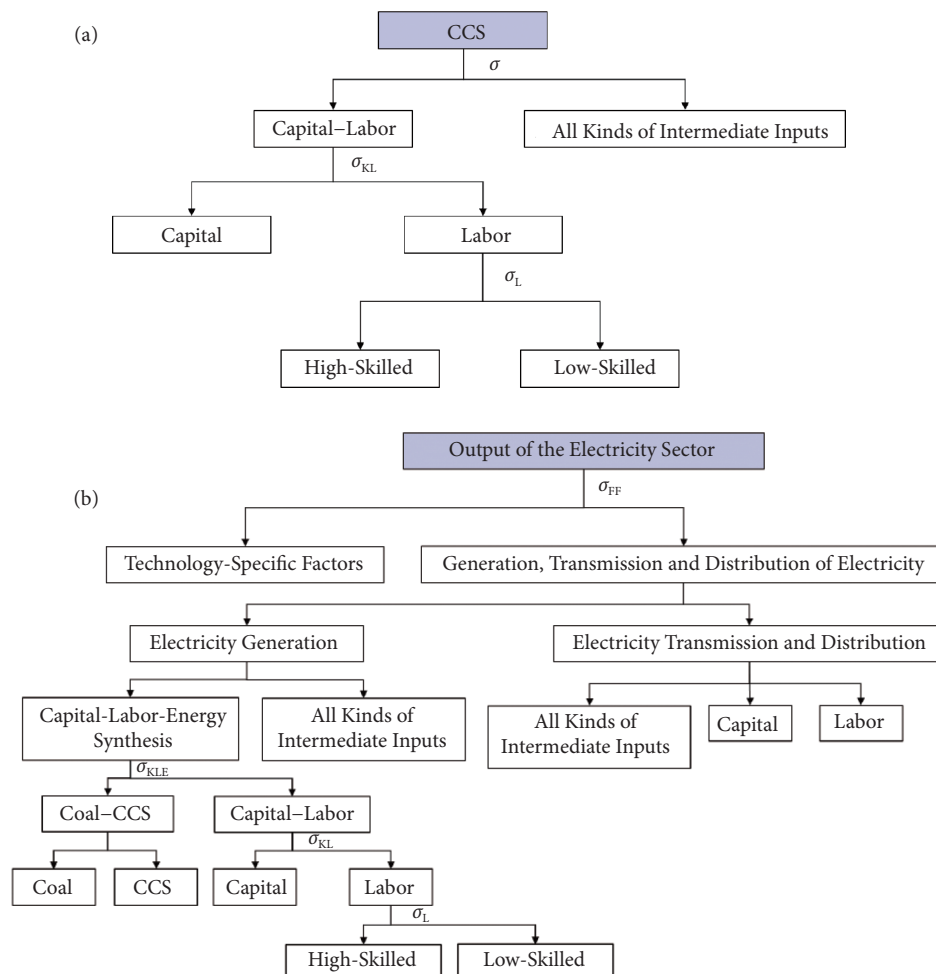


Fig. 2 (a) CCS nested structure and (b) nested structure of coal-fired power CCS technology in the CE3-CGE model.

economic growth, technological transitions, and emission trajectories, enabling detailed exploration of China's long-term low-carbon and negative-emission pathways.

2.1.3 Main modules

CE3-CGE aligns with standard CGE conventions in its remaining assumptions and employs a modular architecture. These modules include: production, trade, consumption, fiscal, factors, technology representation, dynamic, and carbon-related extension modules. The carbon-related extension modules comprise mechanisms such as the carbon emission trading system, China certified emission reduction, and renewable energy subsidies. The modular architecture promotes strong extensibility and enables the straightforward disabling of superfluous modules.

1) Production module. Within the production module, each industrial sector produces a single product under the assumption of constant returns to scale. This module characterizes firm production by modeling how firms transform capital, labor, and intermediate inputs into output. Operating on the profit-maximization assumption, it uses multi-tier nested CES and Leontief functions to describe production technologies and intersectoral input–output relationships. The allocation of the firm's output between exports and domestic sales is described using a constant elasticity of transformation (CET) function. The export portion feeds into the trade module while simultaneously generating tax revenue for the fiscal module. The CET function for allocating production between domestic sales and exports is shown in Eq. (4), where Q denotes the produced quantity, A_q denotes the scale parameter for production, α_q denotes the share of domestic sales, D denotes sales allocated domestically, and E denotes exports.

$$Q = A_q [\alpha_q D^{\rho_q} + (1 - \alpha_q) E^{\rho_q}]^{1/\rho_q} \quad (4)$$

2) Trade module. The trade module assumes that domestic and foreign goods are imperfect substitutes, simulated through CET functions and Armington functions. Products from each industrial sector are allocated partly for domestic consumption and partly for export, as discussed in the production module. Meanwhile, the supply of goods for domestic consumption is composed of domestic output and imports. The trade module generates tax revenue for the fiscal module and is intrinsically linked to domestic and foreign savings, consumption, and investment. Furthermore, the endowment factors module supplies primary inputs to the trade module, while the production module supplies intermediate and final goods. The Armington function for the composite consumption good is specified as Eq. (5). The final consumption good is a composition of a domestic good D , which is also the domestic output supplied locally, and an imported component M , which is the production supplied from other regions and is equivalent to the sum of all other exports to this region. The aggregation is governed by a scale parameter A^c and a share parameter SHR , which specifies the base-year expenditure share on the domestic good.

$$C = A^c [SHR \cdot D^{\rho_c} + (1 - SHR) \cdot M^{\rho_c}]^{1/\rho_c} \quad (5)$$

3) Consumption and fiscal module. The consumption and fiscal module primarily encompasses three economic agents: households, firms, and the government. This module simulates the behaviors of these multiple agents through their respective incomes and expenditures. CES function is typically employed to

describe the household consumption utility function. Household income originates from factor income and transfer payments, while expenditures include consumption, savings, and taxes or fees. Enterprise income mainly consists of factor income, transfer payments, and revenue from product sales; and expenditures primarily involve transfer payments to households, savings, and taxes or fees. Regarding the government, its revenue is chiefly derived from taxation and foreign transfer payments, and its expenditures are mainly allocated to domestic transfer payments, government consumption, and savings. The fiscal component replicates government behavior, covering the tax system, public expenditure, and transfer payments, thereby illustrating how fiscal policy influences macroeconomic stability and resource redistribution. Households and enterprises pay taxes and fees to both local and central governments. The central government makes transfer payments to local governments, which in turn provide transfer payments to households and enterprises. Concurrently, the government also receives tax revenue from the trade and production modules.

4) Factor and dynamic modules. The endowment factors module supplies the labor, capital, and energy resources required for enterprise economic activities to the production module. The dynamic module incorporates recursive dynamic changes considering given labor force growth, endogenous new investment, depreciation, and the evolution of technological progress. The future dynamic changes in this module substantially impact the consumption and production modules.

5) Equilibrium and closure. The various markets described by the aforementioned modules satisfy macroeconomic equilibria, specifically including factor market equilibrium, the government budget balance, the investment–savings equilibrium, and the balance of payments equilibrium. This model adopts neoclassical closure rules. Factor and commodity prices are endogenously determined within the model, while factor supplies are exogenously given, ensuring supply equals demand. On the international front, the exchange rate is exogenous, and foreign savings are determined within the model.

Through this modular, dynamic, and technology-explicit structure, the CE3-CGE model provides a coherent analytical framework for assessing the economic, energy, and emission impacts of China's low-carbon transition at both national and provincial scales.

2.2 PECE model

Complementing the macro-level perspective of the CGE model, the PECE model provides a detailed bottom–up representation of the energy system. It captures sector-specific energy demand, technology options, and transformation processes across industry, buildings, transport, and power sectors. By explicitly modeling technology pathways and their techno-economic characteristics, PECE enables the assessment of sectoral transition dynamics, policy impacts, and investment requirements, thereby strengthening the technological and sectoral resolution of the COMPASS.

2.2.1 Overview

The PECE model is a bottom–up national energy system model. It is a partial equilibrium framework designed to simulate the dynamics of China's energy-economy-environment-society nexus. It centralizes the energy system and offers a comprehensive depiction of technical processes and associated alternatives. This

framework enables the model to analyze technology substitution effects and to assess the ramifications of technological advancement on emissions, energy consumption, and expenses. The fundamental principle of PECE is that sectoral energy service demands are determined by socio-economic drivers such as population and GDP. These demands are then matched with assumptions on future technological development under different scenarios, yielding projections of energy consumption and emissions. The model incorporates a total of 471 technologies^[7], supported by a comprehensive technology database that includes information on performance, efficiency, costs, and emissions. This allows PECE to simulate energy consumption, emissions, abatement costs, and investment requirements across multiple scenarios. The greenhouse gas emissions coverage of the model extends beyond CO₂ from energy use and industrial processes to also include forest carbon sinks and non-CO₂ greenhouse gases, such as CH₄, N₂O, SF₆, HFCs, and PFCs.

The PECE model is implemented on the Low Emissions Analysis Platform (LEAP) platform and offers a detailed characterization of China's energy system, strictly following the energy flow from extraction, conversion, and transportation to final use. The end-use module covers major sectors including industry, buildings, transportation, and agriculture, with further disaggregation into key subsectors, products, and activities. The transformation module encompasses electricity generation and transmission losses, heat production, hydrogen production, coking and gasification, as well as oil refining. PECE not only simulates the entire energy system—from primary energy extraction to conversion and final consumption—but also links it with key dynamic drivers, such as population mobility, macroeconomic and social development, and industrial restructuring. By incorporating project-level financial analysis, the model derives life-cycle marginal abatement costs for energy-saving technologies, equipment, and infrastructure projects. It further connects time-segmented technology and investment roadmaps—targeted at medium-to long-term low-carbon

development—with assessments of effective carbon price levels. In doing so, this model provides critical insights for the design and management of the national carbon market, sectoral low-carbon development planning, project investment strategies, and the formulation of national mid- and long-term low-carbon policies.

2.2.2 Energy demand simulation

A notable characteristic of the PECE model is its improved depiction of driving factors and energy service demand. The model connects end-use service demand with population distribution, urban socio-economic characteristics through the construction of a population submodule. It further captures feedback between production and consumption across end-use sectors, therefore enhancing the evaluation of future trends in population growth, socio-economic development, and energy service demand. To better capture the characteristics and potential impacts of China's urbanization, PECE incorporates a population migration module, dynamically simulating rural-to-urban flows across different city tiers and strengthening the assessment of how population mobility and income growth shape future demand^[8]. It adopts 2020 as the base year and 2060 as the target year. In terms of temporal resolution, the power system employs an hourly-level approach for the electricity system, while other modules operate on an annual scale, with year-by-year simulations conducted throughout the modeling horizon.

In industrial sector modeling, energy-intensive subsectors such as steel, cement, electrolytic aluminum, petrochemicals, and chemicals are modeled separately due to their concentrated energy consumption (Figure 3). For the petrochemical, chemical, and other industrial subsectors, future production and value added are projected using conventional approaches, drawing on population growth, GDP, industrial structure, and per capita output levels relative to those observed in developed economies. By contrast, for key industries such as steel, cement, and electrolytic aluminum, the modeling accounts for their upstream–downstream linkages with construction, transport, and other demand-side sectors.

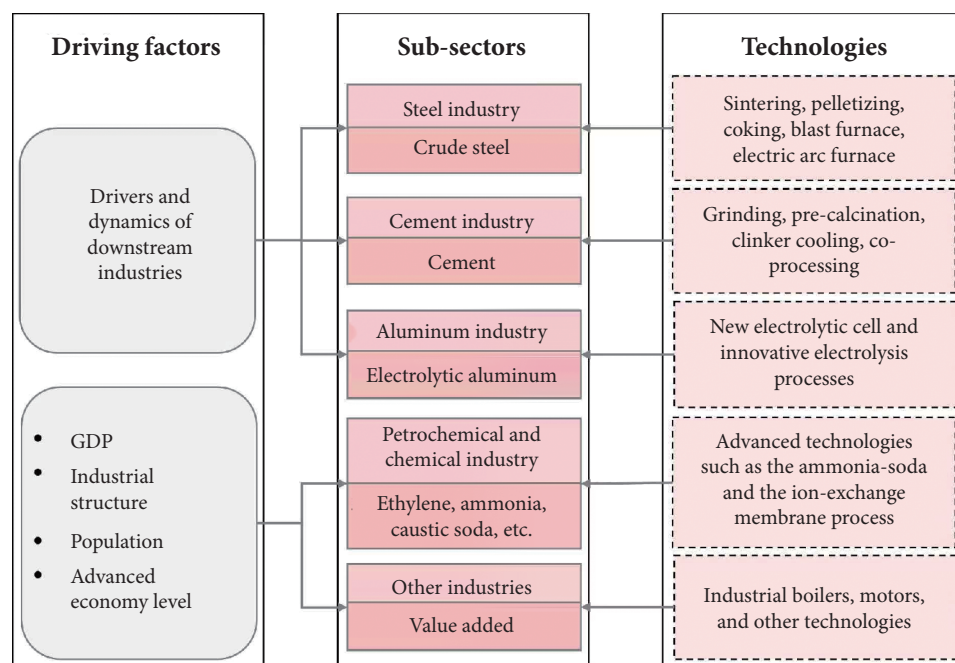


Fig. 3 PECE modeling structure of the industrial sector.

Specifically, it traces how urbanization patterns and demographic changes shape demand for energy services in these downstream sectors—including infrastructure development, building floor area, and vehicle and appliance ownership—and, in turn, projects the future output trajectories of these energy-intensive industries.

In the transport sector, the PECE model distinguishes between passenger and freight transport, with further disaggregation into road, rail, waterway, aviation, and pipeline (for freight) categories^[9]. Road transport, as the dominant source of energy consumption, is subdivided into different vehicle types and travel modes. In total, the transport module incorporates 109 technologies, including fuel efficiency improvements, electric vehicles, and urban rail transit. To examine the implications of prioritizing public transport development, travel demand is further separated into intra-city and inter-city trips. Beyond conventional public transport modes such as buses and railways, an explicit urban rail transit submodule is introduced to assess its modal share in urban trips and associated energy use. To ensure consistency with national statistical conventions, the analysis of international aviation and shipping is restricted to segments operated by domestic companies.

In the building sector, the PECE model comprises modules for urban residential, rural residential, and public and commercial buildings, with a dedicated module for northern urban heating^[10]. Northern heating is modeled separately due to its high energy share and distinct technological characteristics compared with other building subsectors and decentralized heating systems. Each subsector incorporates multiple energy service categories, including heating, cooling, cooking, hot water, lighting, and appliances, while public and commercial buildings additionally

capture office equipment demand. Given the substantial differences in energy intensity between ordinary public buildings and large-scale public facilities, their future development trajectories and energy use are analyzed separately.

2.2.3 Energy conversion and resource modules

The electricity sector is the core of the conversion module. Another key innovation of the PECE model is the explicit integration of electricity load curves, including typical daily profiles for each season, enabling a realistic representation of temporal demand distribution and volatility^[11]. This allows for detailed policy simulations at the grid level, such as assessing how different charging and discharging patterns of electric vehicles may exacerbate peak loads or facilitate peak shaving, and how storage technologies and demand-side management strategies reshape load profiles, thereby altering requirements for new generation capacity. The electricity modeling framework begins by deriving total electricity supply requirements from end-use demand and transmission losses (Figure 4). Based on peak load conditions and reserve margin standards, the model determines the total installed capacity and additional capacity needs associated with demand growth, with national capacity expansion driven primarily by peak daytime loads in summer. Capacity additions for specific technologies are then allocated according to planning objectives and research scenarios. Drawing on historical dispatch patterns, projected generation mixes, and policy targets, each unit is assigned an operational role (e.g., baseload or peaking), from which generation hours, output, fuel use, and emissions are calculated.

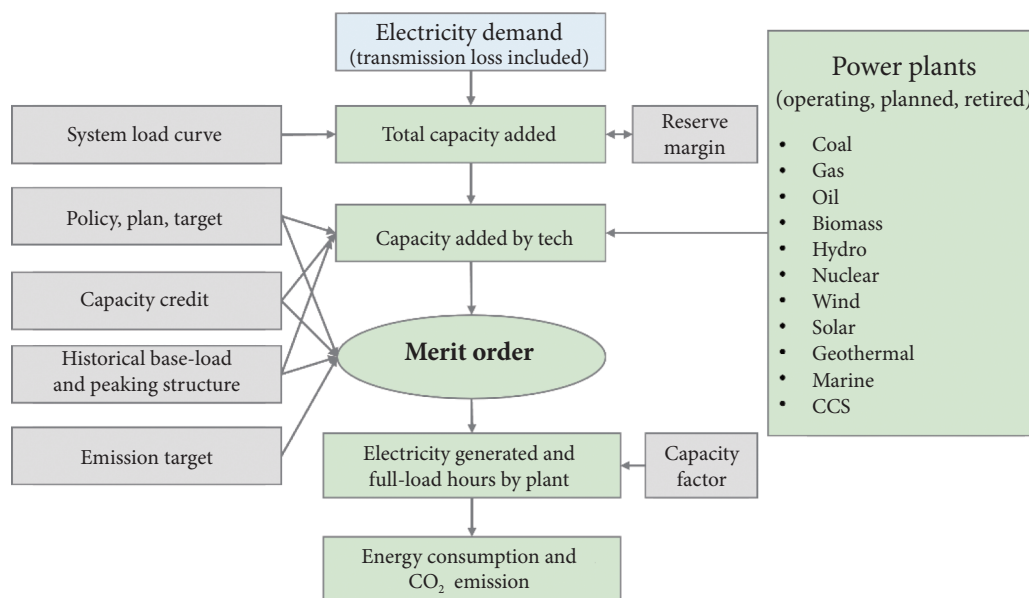


Fig. 4 PECE modeling structure of the power sector.

Other conversion subsectors—including heat generation, coking and gas production, and oil refining—are represented using aggregated technologies calibrated to the energy input–output relationships reported in national energy balance tables. The energy resource module constrains the availability, potential, trade flows, and prioritization of primary and secondary energy supplies. It also incorporates assumptions on imports,

domestic production, and price dynamics to ensure consistency between resource availability and system-level energy demand.

2.2.4 Investment and cost analysis

The PECE model incorporates a comprehensive set of cost parameters, which are categorized into infrastructure, energy efficiency, equipment and end-use fuel substitution, and CCS. To

more accurately reflect the timing of investment decisions aligned with low-carbon development goals, the analysis also accounts for the construction lead times of individual projects. Based on China's climate targets, the model determines sector-specific emissions trajectories across industry, buildings, transport, and power, together with the corresponding levels of infrastructure deployment, technology diffusion rates, and temporal investment distributions. This framework enables the derivation of technology-specific abatement costs in a detailed and dynamic manner. One of the key indicators is the marginal abatement cost (MAC) of low-carbon technologies over their full life cycle. Drawing on methods from financial analysis, the model calculates the incremental cash flows of an investment project relative to conventional technologies, including additional fixed costs, operation and maintenance expenditures, and savings from reduced fuel consumption. By applying a social discount rate, the net present value of incremental costs is derived. Dividing this value by the cumulative emission reductions over the project's lifetime yields the MAC.

For technologies with negative MACs, investments generate net economic benefits even in the absence of a carbon price, implying that enterprises have intrinsic incentives to adopt such technologies. For technologies with positive MACs, an indicator called the cost compensation ratio, $R_{\text{compensate}}$, is introduced to compare the incentive effects of a given carbon price across sectors and technologies, as shown in Eq. (6), where i represents different technologies. This ratio is calculated as the difference between the carbon price and the technology's MAC, divided by the MAC. When $R_{\text{compensate}} < 0$, the revenue from carbon pricing only partially offsets the incremental investment cost; when $R_{\text{compensate}} > 0$, carbon revenue not only covers the additional investment but also generates net profit, thereby encouraging firms to adopt low-carbon technologies and accelerating their diffusion.

$$R_{\text{compensate}} = \frac{\text{Carbonprice} - \text{MAC}_i}{\text{MAC}_i} \quad (6)$$

By quantifying the investment incentives of different carbon price levels, the financial analysis module provides a robust

reference for evaluating carbon market effectiveness. Moreover, the temporal profile of investment requirements allows for projections of long-term carbon price trends, which in turn can inform government strategies for carbon market governance and send credible signals to guide corporate low-carbon investment decisions.

2.3 GCAM-CHN model

The GCAM-CHN model extends the analysis to a comprehensive integrated assessment framework. It links the energy system with land, climate, and resource dynamics, enabling the exploration of long-term transition pathways under different socio-economic and policy scenarios.

2.3.1 Overview

The GCAM model (<https://jgcri.github.io/gcam-doc/index.html>) developed by the Pacific Northwest National Laboratory in the United States is one of leading IAMs globally. GCAM divides the world into 32 regions. China is represented as an independent region, engaging in trade of fossil fuels and agricultural products with other global regions. As an IAM, GCAM covers multiple human and natural systems and describes their interactions and dynamic feedbacks. The core system of GCAM is the energy system, which provides a detailed representation of the entire energy use process, from extraction to end-use. This aspect is similar to the PECE model. To better assess China's medium- and long-term carbon emissions and energy transition pathways, GCAM-CHN is developed based on the GCAM framework to provide a comprehensive, localized, and enhanced representation of China's energy system, along with refined parameterization^[12,13]. As shown in Figure 5, GCAM-CHN integrates a full-chain representation of China's major energy sectors, technologies, and services, and establishes a corresponding localized technology inventory and parameter dataset. This localized model can simulate the impacts of various energy-environmental-economic scenarios on sectoral energy transition, technology development, and carbon emissions in China, thereby providing valuable insights for national low-carbon transition pathway and policy design.

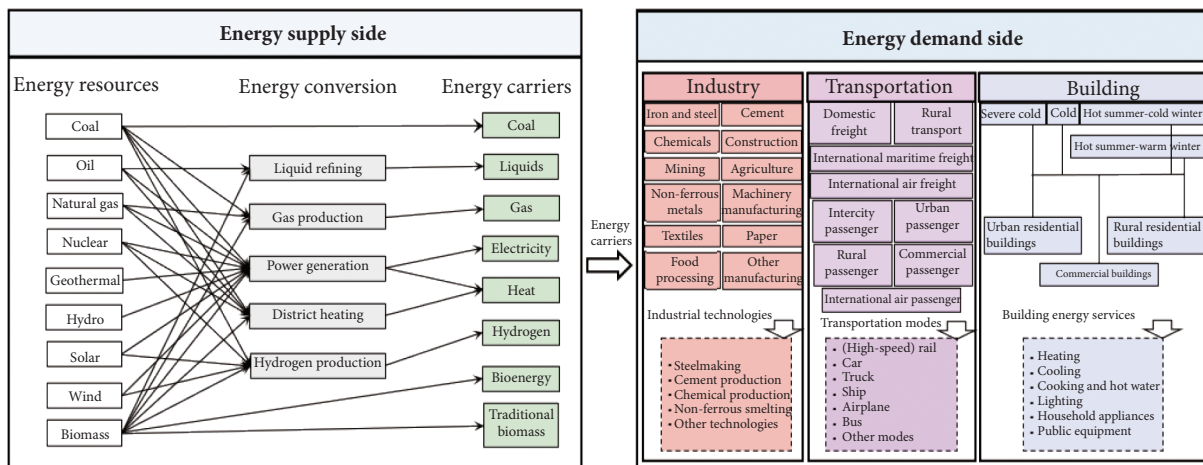


Fig. 5 GCAM-CHN energy system structure.

2.3.2 Energy demand module

On the energy demand side, GCAM-CHN provides particularly detailed representations of China's industrial, transport, and

building sectors, with primary data sources including the IEA Energy Balances, China Statistical Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, China

Transportation Statistical Yearbook, China Building Energy Consumption Research Report, and other relevant literature. Specifically, the industrial sector is disaggregated into 12 subsectors: steel, cement, chemicals, non-ferrous metals, construction, agriculture, mining, machinery manufacturing, textiles, food processing, paper, and other manufacturing industries^[14]. These subsectors encompass a wide range of specific technologies, such as steelmaking technologies (e.g., blast furnace-basic oxygen furnace, electric arc furnace with scrap, direct reduced iron steelmaking), cement production technologies (e.g., cement kiln heating, cement electric mixing), chemical technologies (e.g., fuel heating, chemical feedstock processing), non-ferrous metal smelting technologies (e.g., alumina refining, aluminum smelting), and other industrial technologies (totaling over 40 specific technologies). The industrial sector also incorporates the application of frontier carbon neutrality-support technologies such as CCS and hydrogen. Each technology involves distinct energy and fuel options; for example, steelmaking utilizes a variety of energy carriers, including coal, refined liquid, gas, electricity, and hydrogen. In addition, GCAM-CHN draws on a series of policy documents, such as the “14th Five-Year Plan for a Modern Energy System”, and the “14th Five-Year Comprehensive Work Plan for Energy Conservation and Emission Reduction”, to calibrate assumptions regarding the deployment and phase-out of technologies within the industrial sector.

The energy service demand of the industrial sector is estimated based on a demand elasticity equation, and is mainly influenced by population, income level, energy service prices, and the income and price elasticity coefficients, as shown in Eq. (7). Here, D_t denotes the energy service demand in period t ; Y_t denotes per capita GDP in period t ; P_t denotes the energy service price in period t ; N_t denotes the population in period t ; and α_t denotes the income elasticity in period t , reflecting the change in demand caused by changes in income. In GCAM-CHN, α_t is adjusted to ensure that the model output aligns with the expected level of industrial demand. β_t denotes the price elasticity in period t , reflecting the change in demand caused by changes in service prices. Generally, as prices increase, the demand for energy services declines.

$$D_t = D_{t-1} (Y_t/Y_{t-1})^{\alpha_t} (P_t/P_{t-1})^{\beta_t} (N_t/N_{t-1}) \quad (7)$$

Given China's vast territory and the significant climatic differences between the north and south, GCAM-CHN subdivides China into four climate zones for building sector modeling: severe cold, cold, hot summer–cold winter, and hot summer–warm winter^[15]. To account for differences in energy consumption scale, characteristics and technologies between urban and rural buildings, GCAM-CHN further classified China's buildings into three types: rural residential buildings, urban residential buildings, and commercial buildings. By combining climate zones and building types, a total of twelve building subsectors are represented. Each subsector includes five categories of energy services: heating, cooling, cooking and hot water, lighting, and household appliances (residential buildings) or public equipment (commercial buildings). These services are provided by various specific technologies; for example, heating can be supplied by electricity, heat, coal, gas, and ground-source heat pumps. Due to variations in climatic conditions, population density, income levels, and building insulation, the demand for different energy services varies significantly across building subsectors.

Building energy service demand mainly depends on population size, per capita building floorspace, and energy service demand per unit floorspace. Since per capita building floorspace and per-unit-floorspace energy service demand tend to gradually saturate as income increase, saturation functions are used to project their future trends. The saturation function for per capita building floorspace is given in Eq. (8). Here, q_t denotes per capita building floorspace in period t ; s and a denote the saturation level and minimum levels of per capita floorspace, respectively; and μ is the saturation damping factor, reflecting the income level corresponding to half of the saturation floorspace. The saturation function for energy service demand per unit floorspace is shown in Eq. (9). Here, d_t denotes the per-unit-floorspace energy service demand in period t ; k denotes the calibration coefficient; and S denotes the saturation level of per-unit-floorspace energy service demand.

$$q_t = (s - a) \left(1 - \exp \left(-\frac{\ln 2}{\mu} Y_t \right) \right) + a \quad (8)$$

$$d_t = k \cdot S \cdot \left(1 - \exp \left(-\frac{\ln 2}{\mu} \frac{Y}{P_t} \right) \right) \quad (9)$$

GCAM-CHN characterizes the transport sector in the form of “subsector-mode-powertrain”, and disaggregates it into four freight subsectors (domestic freight, rural transport, international maritime freight, and international air freight) and five passenger subsectors (intercity passenger, urban passenger, rural passenger, commercial passenger, and international air passenger)^[16]. GCAM-CHN encompasses 20 specific transport modes, including private cars, high-speed rail, trains, buses, motorcycles, trucks, ships, airplanes, walking, bicycles, and subways, and covers five powertrain systems. Similar to the industrial sector, GCAM-CHN localizes and calibrates the parameters of China's future transport system based on a series of transport-related policy documents, such as the “New Energy Vehicle Industry Development Plan (2021–2035)”, and the “Medium- and Long-Term Plan for Hydrogen Industry Development (2021–2035)”. Transport development is driven by transport service demand, which is primarily determined by household income, economic scale, and transport service prices. Passenger service demand is also calculated using Eq. (7), while freight service demand is calculated using Eq. (10), where G_t denotes GDP in period t .

$$D_t = D_{t-1} (G_t/G_{t-1})^{\alpha_t} (P_t/P_{t-1})^{\beta_t} \quad (10)$$

2.3.3 Energy supply module

On the energy supply side, GCAM-CHN specifically calibrates and updates techno-economic parameters for sectors such as power generation, hydrogen production, heat supply, oil refining, and gas production to reflect China-specific conditions. The power sector provides detailed representations of various power generation technologies. Fossil power generation primarily includes coal-fired and natural gas-fired generation, covering conventional generation, integrated gasification combined cycle, and other technologies, all of which can be equipped with CCS, resulting in a total of ten specific technologies. Non-fossil power generation includes solar, wind, hydropower, biomass, nuclear, and geothermal energy. Among them, solar power includes centralized photovoltaics, distributed rooftop photovoltaics, and concentrated solar power, while wind power includes both

offshore and onshore wind, with optional energy storage systems for solar and wind generation. Biomass power includes conventional generation and combined cycle generation, which, when combined with CCS, can deliver negative carbon emissions for the energy system. In recent years, the cost of renewable energy generation in China has dropped significantly, with particularly pronounced declines in solar and wind power costs. To reflect these localized trends, GCAM-CHN updates parameters for each power generation technology in China's power sector, including overnight capital costs, capacity factors, and expected lifetimes^[17]. In the hydrogen production sector, GCAM-CHN provides detailed representations of seven hydrogen energy carriers: coal, natural gas, biomass, grid electricity, nuclear, solar, and wind. Hydrogen is mainly applied in the industrial and transport sectors. In the industrial sector, hydrogen not only serves as an efficient fuel for various thermal processes, boiler steam, and mechanical drives, but can also be used as a feedstock in steelmaking, chemical production, and nitrogen fertilizer production.

Since GCAM-CHN is a partial equilibrium model, the overall energy consumption demand determines the energy supply. Specifically, the supply of energy carriers such as electricity, hydrogen, heat, liquid, and gas is primarily influenced by the market shares of the corresponding energy technologies. The market share of each energy carrier/technology ($share_{it}$) is determined by the logit function^[18], as shown in Eq. (11). Here, p_{it} denotes the levelized cost of energy carrier/technology i in period t , which consists of energy costs (energy prices are endogenously determined in the model; and carbon-related costs are added under carbon constraints) and non-energy costs (set exogenously); sw_{it} denotes the share weight of energy carrier/technology i in period t (set exogenously), reflecting policy or market preferences; and γ is the price elasticity coefficient. This market share competition approach is based on the principle of cost optimization while avoiding a winner-takes-all outcome. In addition, sw_{it} is also used to calibrate the model's historical simulation results. GCAM-CHN adjusts parameters such as share weights and elasticity coefficients to ensure that the simulated energy consumption and energy structure are generally consistent with recent statistical data.

$$share_{it} = \frac{sw_{it} \cdot p_{it}^{\gamma}}{\sum_i sw_{it} \cdot p_{it}^{\gamma}} \quad (11)$$

2.4 Hybrid econometric-machine learning models

In addition to structural models, the COMPASS incorporates econometric and machine learning approaches to provide data-driven insights and empirical validation.

2.4.1 Overview

Rooted in economic theory, econometric models are designed to uncover causal relationships and elucidate underlying economic mechanisms among variables. They provide a foundational framework for analyzing economic phenomena, interpreting mechanisms in energy and climate change economics, and evaluating policy impacts. The main methodology involves constructing structured equations to translate economic theories into quantifiable mathematical forms, enabling the identification of causal effects of specific variables and the testing of theoretical hypotheses. A key strength of econometric approaches lies in their

emphasis on model interpretability, unbiased estimation, and rigorous statistical inference—all essential for deriving reliable economic interpretations and policy-relevant insights. However, these methods rely heavily on correct model specification and often face limitations in handling high-dimensional data and complex nonlinear relationships.

From the perspective of model architecture, traditional econometric methodology has established a logically rigorous and application-mature framework of modeling techniques. Specifically, the Vector Autoregression (VAR) model, by virtue of its capacity to capture dynamic interdependencies among multiple variables, effectively characterizes bidirectional feedback effects and lagged transmission mechanisms within economic systems. It is widely used in empirical research to identify the dynamic transmission pathways of exogenous shocks—such as energy price fluctuations—through macroeconomic systems. Furthermore, through impulse response functions and variance decomposition, the VAR model enables quantitative analysis of the magnitude and persistence of such shocks^[19]. In the study of the micro-level mechanisms of regional economic development, panel data models offer distinct advantages. By integrating information from both time-series and cross-sectional dimensions, these models can incorporate individual or time fixed effects to effectively control for unobserved individual heterogeneity and time-varying confounding factors. This allows for more accurate estimation of the average treatment effect in policy evaluation, reducing biases resulting from omitted variables in single-dimensional data^[20]. Furthermore, classical econometric methods for causal inference—including Instrumental Variable Regression (IV), Regression Discontinuity Design (RDD), and Difference-in-Differences (DID)—play a central role in policy evaluation and mechanism identification. Among these, IV regression addresses endogeneity issues between explanatory and explained variables by employing instruments that are highly correlated with the core explanatory variable and satisfy exogeneity assumptions^[21]. RDD leverages policy-induced discontinuities to create quasi-experimental designs, enabling precise identification of local average treatment effects^[22]. DID, meanwhile, constructs a comparative framework between treatment and control groups, isolating policy effects from underlying time trends and providing a robust strategy for estimating net policy impacts.

Machine learning models, which originated from computer science, are fundamentally data-driven in nature. They excel at identifying hidden patterns and correlations in large-scale datasets, with a primary emphasis on optimizing predictive accuracy and enhancing model fitting capabilities. This category encompasses a diverse set of algorithms, including supervised and unsupervised learning, which operate without relying on rigid theoretical assumptions. Capable of automatically processing high-dimensional, heterogeneous data and capturing intricate nonlinear relationships, such models demonstrate strong adaptability to diverse data structures and deliver high predictive performance^[23]. In the field of resource and environmental economics, machine learning is increasingly employed to address complex analytical and predictive challenges. For example, it facilitates high-resolution environmental monitoring through satellite imagery analysis for applications such as deforestation tracking, air pollution mapping, extreme weather forecasting, and water quality assessment^[24,25]. Machine learning methods are also utilized in energy load forecasting, long-term climate impact

projection, and evaluating the effectiveness of policy interventions^[26]. Furthermore, these techniques enable the analysis of heterogeneous policy effects across regions, the identification of nonlinear ecological tipping points, and the enhanced simulation of coupled human-natural systems. Despite these advancements, the high predictive performance of machine learning often comes at the expense of interpretability, leading to their characterization as “black-box” systems. This limitation poses a particular challenge in policy design, where transparency and causal interpretability are essential for informed decision-making.

2.4.2 Hybrid system

Integrating econometric with machine learning models establishes a comprehensive analytical paradigm covering impact assessment, mechanism analysis, and trend forecasting, thereby providing a powerful methodology for addressing complex challenges in energy and environmental research^[27]. Within this hybrid system, the econometric module focuses on identifying key drivers, elucidating causal mechanisms, and generating structurally informed predictions grounded in economic theory. The machine learning module is dedicated to selecting high-dimensional features, detecting nonlinear patterns, and improving predictive accuracy through optimization and calibration techniques. By leveraging their complementary advantages, the hybrid system not only improves the adaptability to real-world complexity, but also improves the robustness, transparency, and policy relevance of research results.

The integration of econometrics and machine learning mainly follows two complementary pathways. The first pathway employs machine learning to empower econometric analysis: algorithms such as LASSO are used for variable selection and dimensionality reduction, which effectively reduce subjective bias and multicollinearity prior to specifying econometric models. Techniques like gradient boosting trees and neural networks capture complex nonlinearities and interaction effects among variables, the outputs of which can either be incorporated as constructed features into conventional models or used as a basis for the specification of more flexible functional forms. In addition, machine learning approaches—including generalized random forests—support more robust causal identification by estimating heterogeneous treatment effects with enhanced adaptability. The second pathway involves enriching machine learning with econometric theory: for instance, incorporating economic priors as structural constraints during model training to ensure predictions align with theoretical expectations rather than relying solely on statistical correlations. Additionally, econometrics-based interpretability tools, such as Shapley value decomposition, clarify the predictions of black-box models by quantifying variable contributions, thereby bridging predictive accuracy and causal mechanisms.

2.4.3 Role within COMPASS

In the COMPASS, econometric models are primarily designed to supply core models with empirically grounded behavioral parameters and external conditions, thereby moving beyond purely theoretical assumptions or static calibration. In contrast, machine learning methods specialize in extracting nonlinear relationships and critical pathways from the large-scale, high-dimensional, multi-scenario output data—often characterized by long time series—generated by complex models. These two

channels are inherently complementary: econometric models strengthen the empirical foundation and policy relevance of the core models, while machine learning techniques enhance their capacity for output analysis and computational efficiency. Together, they form a chain that spans parameter estimation, scenario analysis, and pattern discovery.

Specifically, using historical data and causal inference methods, econometric models can estimate structural parameters that align with economic theory. For the CE3-CGE model, such parameters may include sector-specific productivity trends, price and income elasticities, policy response parameters, carbon-price expectations, and observed responses of firms or households to environmental regulation. For the GCAM-CHN model, econometrically estimated income elasticities and technology diffusion rates can be directly incorporated into the model, influencing baseline projections of energy service demand and technology transition pathways. Moreover, methods such as event studies or regression discontinuity design allow econometric models to quantify short-term responses following the implementation of specific policies. The estimated magnitudes and decay patterns of these shocks can then be translated into policy shock parameters within the CGE model, thereby improving its ability to replicate real-world policy effects.

On the other hand, using large-scale simulation and observational data, machine learning methods can identify nonlinear patterns and critical thresholds in complex systems. For the GCAM-CHN or PECE model, algorithms such as random forests or gradient boosting trees can rank feature importance across multi-scenario outputs and automatically detect critical variable thresholds that trigger abrupt system state transitions. Through dimensionality reduction techniques—such as principal component analysis or autoencoders—high-dimensional outputs can be compressed into a small number of composite indicators. When combined with sequence matching methods like dynamic time warping, this approach enables the selection of simulation pathways that most closely align with real-world dynamic patterns. Furthermore, by using the extensive outputs of core models as training data, machine learning metamodels (e.g., neural networks or random forests) can be constructed to predict key outputs under new scenarios—such as carbon emission peaks or transition costs—in near real time, without the need to run the full complex model. This significantly reduces the computational burden associated with multi-scenario analysis and facilitates broader parameter sensitivity analysis and uncertainty quantification.

3 Discussion

3.1 Model application

The COMPASS developed by the School of Ecology & Environment, Renmin University of China covers multiple spatial scales, ranging from global multi-regions to China's national, provincial, and sectoral levels. The COMPASS enables multi-tier, multi-dimensional, and multi-period policy simulations in the fields of energy and climate governance, providing customized decision support for policy formulation. In alignment with national strategic needs, the School of Ecology & Environment, Renmin University of China has extensively applied these models to research on climate policy, energy policy, and market mechanisms. Some typical applications are provided in Table 1.

Specifically, the CE3-CGE model has been applied to simulate the impacts of China's carbon market on the economy, environment, and social welfare, revealing the role of carbon trading in regulating emissions as well as the regional and sectoral heterogeneity of carbon abatement costs^[28]. The model has also been used to assess the potential differentiated impacts and mitigation consequences of carbon tax policies across the national economy, regions, and industries, as well as to simulate the comprehensive effects of environmental regulation policies (e.g., environmental taxes, and ecological compensation) on both the economy and the environment^[3,29]. By coupling the CE3-CGE model with a bottom-up model, the economy-wide benefits of market-oriented power sector reforms in China were quantified, demonstrating that transitioning to merit-order dispatching yields significant macroeconomic gains through lower electricity prices^[30]. This linked modeling approach has been further extended to evaluate the carbon mitigation potential, local pollutant co-benefits, and economy-wide impacts of China's deep decarbonization pathways, providing integrated evidence that environmental health co-benefits can substantially offset the economic costs of decarbonization^[31]. Research based on CE3-CGE has provided strategic references for building a more efficient, more vibrant, and more internationally influential carbon market in China, as well as for considering the design of carbon taxation^[6]. In addition, this model is being integrated with an environmental quality and health module^[32], thereby enabling high-resolution health assessments of life expectancy, morbidity and mortality, and health effects on both the production and consumption sides.

The PECE model has been employed to quantitatively analyze China's medium- and long-term low-carbon energy transition pathways under carbon peaking and carbon neutrality, as well as the Paris Agreement 2 °C and 1.5 °C goals^[33,34]. The model has supported sector- and process-level decarbonization planning and

technology deployment roadmaps^[8–11,35], evaluated the cost-benefit and mitigation potential of key abatement technologies, and estimated the investment needs and gaps^[33]. Recently, the PECE model was applied to examine the timeline of China's carbon peaking under the comprehensive implementation of the "1+N" policy framework^[7]. Scenario analyses based on PECE have provided useful support for designing China's carbon peaking and carbon neutrality strategies, as well as its 2035 Nationally Determined Contributions.

The GCAM-CHN model, which incorporates localized improvements to China's energy system, has also been applied to China's energy transition studies. The sectoral coverage of GCAM-CHN studies has included power, oil and gas, industry, buildings, and transport^[13,14,16,17], while the technology coverage has encompassed wind, solar, biomass, nuclear, electric vehicles, CCS, BECCS, DACCS, hydrogen, and many other zero- and negative-emission technologies^[16,17,36,37]. More recently, the model was linked with micro-level methodologies such as input–output analysis, life-cycle assessment, and questionnaire survey to study issues such as the CBAM costs faced by China's metal industry^[38] and the carbon assets in China's agroforestry biomass power generation^[39]. These studies are expected to open new directions for integrating macro- and micro-level modeling.

Furthermore, integrated econometric and machine learning models has been employed to generate short-term forecasts of China's carbon prices, assess the mitigation effects of the carbon market across regional, industrial, and enterprise levels, and analyze the impacts of environmental policies on green innovation and total factor productivity^[22,40]. These models have also been utilized to examine the broader socio-economic impacts of climate change and air pollution, spanning GDP growth, agricultural output, mortality, subjective well-being, income inequality, employment, and population migration^[20,41].

Table 1 Summary of typical model applications

Model name	Typical applications	Representative references
CE3-CGE	Carbon pricing, emissions trading, carbon tax design, fiscal recycling, regional and sectoral impacts of climate policies, economy-wide assessment of low-carbon transition, and policy cost assessment	[6, 29, 32]
PECE	Sectoral transition pathways, policy impact assessment for low-carbon transition, and techno-economic analysis of low-carbon technologies	[7, 33, 35]
GCAM-CHN	Energy transition scenarios, sectoral decarbonization pathways; technology deployment trajectories, and mitigation policy assessment	[13, 17, 37]
Econometric and machine learning models	Carbon pricing, socio-economic impacts of low-carbon transition, and policy impact assessment	[19, 21, 22]

3.2 Model integration and soft-linking protocols

Beyond their individual applications, these four types of models are increasingly integrated through soft-linking protocols, enabling more coherent and refined multi-model research. Such linkages allow the strengths of different modeling paradigms—macroeconomic consistency, technological detail, empirical grounding, and data-driven exploration—to complement one another. The CE3-CGE, PECE, and GCAM-CHN models have been jointly applied in comparative assessments and cross-validation of China's energy transition scenarios, with both CE3-CGE and GCAM-CHN participating in multi-model comparisons organized by the China Energy Modeling Forum (CEMF). By

iteratively reconciling macroeconomic and energy system data^[28], the top-down CE3-CGE model is soft-linked with the bottom-up PECE or GCAM-CHN model, thus capturing system-wide economic feedbacks while preserving the technological granularity of sectoral models. This coordination facilitates a consistent understanding of policy impacts from macroeconomic adjustments down to specific technology pathways. Specifically, within the COMPASS, each model retains its own methodological structure while passing selected outputs to other models as exogenous assumptions, calibration targets, or validation benchmarks.

First, as mentioned earlier, econometric and machine-learning models provide empirically estimated parameters and short-term

projections for the CGE and energy-system models. Taking CE3-CGE as an example, these estimates can be used to update exogenous assumptions on total factor productivity, substitution elasticities, demand elasticities, and policy shock parameters. In addition, machine-learning-based forecasting of energy prices, carbon prices, or technology diffusion trends can provide near-term boundary conditions for scenario design.

Second, PECE provides technology-level information that can be used to inform technology representation in GCAM-CHN and CE3-CGE. Typical outputs from PECE include technology-specific MACs, investment requirements, energy efficiency improvements, fuel-switching potentials, technology deployment constraints, and sectoral emissions trajectories. These outputs can be translated into GCAM-CHN through adjustments to technology costs, share weights, deployment constraints, and sectoral service-demand assumptions. For CE3-CGE, PECE outputs can be aggregated into sector-level abatement cost curves, technology investment shocks, energy-efficiency parameters, or changes in the input structure of energy-intensive sectors.

Third, GCAM-CHN provides long-term system-level pathways that can serve as scenario envelopes for CE3-CGE and PECE. These include national and sectoral emissions pathways, energy-mix trajectories, fuel prices, carbon prices, hydrogen and electricity demand, negative-emission deployment, and cross-sectoral technology transitions. These results can be used to define long-term carbon-neutrality scenarios, constrain sectoral emissions trajectories, or test whether technology roadmaps generated by PECE are consistent with broader energy-system and climate constraints.

Fourth, CE3-CGE provides economy-wide feedbacks to the bottom-up and integrated models. Its outputs include GDP, sectoral output, industrial structure, household income, energy demand, regional economic impacts, welfare changes, and carbon-price effects. These outputs can be used to revise socio-economic assumptions, sectoral activity levels, and demand-side drivers in PECE and GCAM-CHN. This is particularly important when climate or energy policies produce significant macroeconomic feedbacks that cannot be captured by bottom-up models alone.

The general handshake protocol therefore follows an iterative sequence: 1) harmonize baseline socio-economic, energy, and emissions data across models; 2) use econometric and machine-learning models to estimate key behavioral and policy-response parameters; 3) run PECE and GCAM-CHN to generate technology pathways, energy-system transformations, and emissions trajectories; 4) pass aggregated technology costs, energy prices, investment requirements, and sectoral activity assumptions to CE3-CGE; 5) use CE3-CGE to estimate macroeconomic and regional feedbacks; and 6) feed updated GDP, sectoral output, energy demand, and income trajectories back to PECE and GCAM-CHN until major scenario indicators converge within an acceptable range. Through this soft-linking structure, the COMPASS combines the strengths of bottom-up technological detail, top-down macroeconomic consistency, integrated long-

term system representation, and empirical parameter estimation. This improves the internal consistency of scenario assumptions, enhances the credibility of policy simulations, and enables a more comprehensive assessment of China's carbon-neutral transition.

3.3 Policy implications and future research directions

The policy value of the COMPASS extends beyond the capabilities of individual models by enabling the analysis of complex policy challenges across scales, mechanisms, and time horizons. The COMPASS allows for the simultaneous assessment of policy impacts on economic structure, technology substitution, and cross-sectoral and regional transmission, thereby capturing systemic interactions along the energy-environment-economy nexus. It also enables cross-validation of key parameters and scenarios, reducing model-specific biases and improving the robustness of policy evaluation. Importantly, the COMPASS supports the assessment of policy interactions across instruments, including carbon markets, subsidies, and technology policies, and ensures consistency between short-term dynamics and long-term transition pathways. This provides a more coherent and policy-relevant analytical basis for decision-making.

Future research could advance toward deeper integration of the modeling system. This requires strengthening data exchange and feedback mechanisms across models and moving from soft-linking toward tighter integration. Moreover, further efforts are required to connect multiple spatial scales, from global to technological levels, and to align short-term dynamics with long-term pathways. The integration of big data and artificial intelligence methods will be critical for capturing high-dimensional heterogeneity, nonlinear relationships, and uncertainty. In parallel, closer linkage with micro-level approaches, such as firm behavior analysis, can strengthen the empirical foundations of policy assessment. These developments will enhance the precision and credibility of model-based support for climate governance and sustainable development.

Despite these advances, challenges remain in the context of model integration. In particular, the transmission of data and parameters across models may still introduce some inconsistencies and additional sources of uncertainty. Differences in model structure, scale, and representation can lead to deviations in information flows and affect the coherence of integrated results. In addition, long-term scenario analysis remains sensitive to exogenous assumptions, including technological progress and policy stringency, which may propagate unevenly across the integrated system. Addressing these issues requires continued efforts to improve data consistency, integration strategies, and the systematic treatment of uncertainty.

Appendix 1. Detailed overview of the COMPASS hosted by School of Ecology & Environment, Renmin University of China.

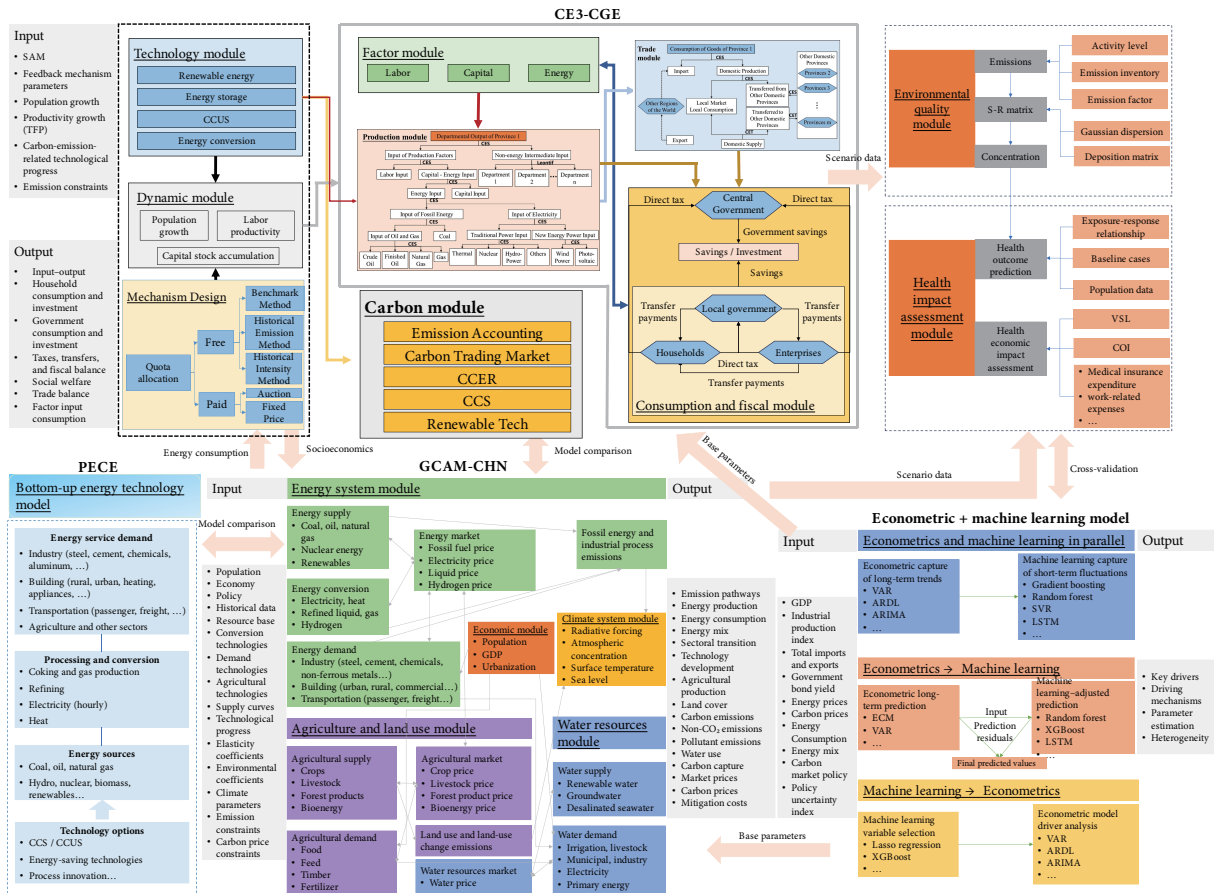


Fig. A1 Detailed overview of the COMPASS hosted by School of Ecology & Environment, Renmin University of China.

Appendix 2. Nomenclature

Abbreviations

CCS	Carbon capture and storage
BECCS	Bioenergy with carbon capture and storage
DACCS	Direct air capture with carbon capture and storage
CES	Constant elasticity of substitution
CET	Constant elasticity of transformation
CGE	Computable general equilibrium
IAM	Integrated assessment model
MAC	Marginal abatement cost
SAM	Social accounting matrix
TFP	Total factor productivity

CE3-CGE model — CES production structure

A_{CCS}	Scale parameter for CCS technology in the CES production function
INT	Intermediate inputs composite
α	Share parameter in the CES function
σ	Elasticity of substitution; $\sigma = 1/(1 - \rho)$
ρ	Substitution parameter; $\rho = 1 - 1/\sigma$
KL	Capital-labor composite endowment factor (CES aggregation of K and L)
K	Capital input
L	Total labor input

L_H	High-skilled labor
L_L	Low-skilled labor

CE3-CGE model — production and trade modules

Q	Total quantity produced by a sector
A_q	Scale parameter for the CET production-allocation function
α_q	Share parameter for domestic sales in the CET function
D	Quantity of output allocated to domestic sales
E	Quantity of output allocated to exports
A_c	Scale parameter for the Armington composite consumption good
SHR	Base-year expenditure share on the domestic good in the Armington function
M	Imported goods (sum of exports from all other regions to this region)

PECE model — investment and cost analysis

$R_{\text{compensate}}$	Cost compensation ratio; (carbon price – MAC) / MAC, measuring the net incentive of a given carbon price
i	Technology index (subscript distinguishing individual low-carbon technologies)

GCAM-CHN model — energy service demand

D_t	Energy service demand in period t
Y_t	Per capita GDP in period t (CNY·person ⁻¹)
P_t	Energy service price in period t
N_t	Population in period t (persons)
α_t	Income elasticity of energy service demand in period t ; adjusted to align model output with expected demand
β_t	Price elasticity of energy service demand in period t ; demand falls as price rises
G_t	GDP in period t ; driver for freight service demand (Eq. 10) (CNY)

GCAM-CHN model — building sector saturation functions

q_t	Per capita building floorspace in period t (m ² ·person ⁻¹)
s	Saturation level of per capita building floorspace (m ² ·person ⁻¹)
a	Minimum level of per capita building floorspace (m ² ·person ⁻¹)
μ	Saturation damping factor; income level at which per capita floorspace equals half the saturation value
d_t	Per-unit-floorspace energy service demand in period t
k	Calibration coefficient for per-unit-floorspace energy service demand
S	Saturation level of per-unit-floorspace energy service demand

GCAM-CHN model — market share logit function

share_{it}	Market share of energy carrier/technology i in period t
p_{it}	Levelized cost of energy carrier/technology i in period t ; includes energy, non-energy, and carbon-related costs
sw_{it}	Share weight of energy carrier/technology i in period t ; set exogenously to reflect policy/market preferences and calibrate historical results
γ	Price elasticity coefficient in the logit market-share function

Acknowledgements

This study was supported by the Major Program of the National Social Science Foundation of China (24&ZD105).

Author contribution statement

Jun Pang conceived and designed the study. All authors contributed to manuscript preparation and revision, and approved the submitted version.

Data availability

Not applicable.

Use of AI statement

During the preparation of this work, the authors used ChatGPT (OpenAI) to improve the English language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of this publication.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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