

IMACLIM-China-MORE: A hybrid model for analyzing greenhouse gases neutrality pathways

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ABSTRACT

Designing effective carbon-neutrality policy for China requires models that capture interactions between technology-oriented energy transitions and economy-wide responses. However, most assessments use either bottom-up energy models or top-down computable general equilibrium (CGE) models in isolation, which limits pathway insights. We develop IMACLIM–China-MORE, an iteratively coupled hybrid model that links the TIMES-based China-MORE 2.0 energy-system optimization model with IMACLIM-CHN, a single-region, 18-sector CGE model. The two models exchange prices, energy-service demands, activity levels, and abatement schedules under harmonized accounts, and the coverage extends from CO₂ to methane, nitrous oxide, and fluorinated gases. We apply the framework to three scenarios: Current Policies, CO₂ Neutrality, and Greenhouse Gas (GHG) Neutrality. Under CO₂ Neutrality, the power and industrial sectors deliver the largest near-term reductions, but about 1.5 GtCO₂e non-CO₂ emissions remain in 2060. Under GHG Neutrality, net-zero CO₂ is achieved by around 2055 and non-CO₂ emissions fall to about 0.8 GtCO₂e in 2060, which would need to be offset by carbon-removal options. The additional macroeconomic costs of moving from CO₂ to GHG neutrality are moderate overall, although the agriculture and food sectors face relatively larger impacts, and investment in the energy system increases by about one third. IMACLIM–China-MORE provides a transparent, policy-relevant platform to evaluate trade-offs among technology choices, macroeconomic outcomes, and multi-gas mitigation on China's path to GHG neutrality.

KEYWORDS

Climate policy, energy-economy hybrid model, CO₂ neutrality, GHG neutrality, transition pathway, China.

1 Introduction

Robust energy and climate policymaking requires a modeling framework that consistently captures interactions between the energy system and the wider economy. Computable general equilibrium (CGE) models and energy-system optimization models are widely used to inform decisions—including nationally determined contributions (NDCs) and carbon-neutrality strategies—but each has limitations that constrain comprehensive assessment^[1,2]. CGE models (top-down) provide a rigorous general-equilibrium perspective, ensuring internally consistent prices and price-responsive behavior across sectors and agents^[3–6]. Yet they lack technological granularity and typically represent technology substitution via elasticity parameters whose empirical values are scarce and uncertain—especially for emerging technologies—limiting their usefulness for technology-specific policy analysis^[5,7,8]. By contrast, bottom-up energy-system models offer detailed representations of energy conversion, transport, and end use, enabling fine-grained technology pathway analysis^[1,9,10]. However, as partial-equilibrium tools, they usually omit feedbacks between the energy sector and the broader economy, thus constraining assessment of economy-wide implications^[11]. These complementary strengths and weaknesses motivate hybrid approaches that combine technological detail with general equilibrium analysis within a single, coherent modeling framework^[12,13].

Three hybrid approaches have been adopted in the literature to combine bottom-up models and top-down models^[7,14]: (i) model coupling, which iteratively exchanges key variables between standalone models so that each model solves in its own framework while converging toward a consistent scenario^[12,13,15,16]; (ii) embedded reduced-form, which treats one model as the core model and represents the other through a calibrated simple module (e.g., an energy-system model with an aggregated macroeconomic block, or macro feedback functions embedded in a bottom-up optimization model)^[17–19]; and (iii) full integration via mixed complementarity, which nests activity-level technology detail within a CGE model by formulating the joint system as a Mixed Complementarity Problem (MCP)^[11].

Although hybrid modeling approaches were initially developed in the context of energy and climate policy, bottom-up and top-down coupling has since been widely applied across environmental economics. Examples include linking biophysical crop models with economic trade models to examine competition between bioenergy and food production^[20], integrating climate-impact models with regional CGE frameworks to assess the macroeconomic consequences of climate risks^[21], and coupling material flow analysis with economic models to explore recycling pathways and resource-efficiency strategies^[22]. These examples demonstrate that bottom-up and top-down coupling represents a general methodological paradigm in environmental-economic analysis. Table 1 details the advantages and disadvantages, current development, and applications of these three types of hybrid

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Table 1 Comparison of three hybrid modeling approaches.

Coupling approaches	Model coupling (method used in this study)	Embedded reduced-form	Full integration
Description	Separate top-down and bottom-up models linked through iterative exchange of key variables until convergence.	Simplified response functions (emulators) extracted from one model and embedded in another model.	Joint formulation of technological and economic constraints within a single mathematical framework (e.g. MCP).
Advantages	Preserves full structure of both models; balances technological detail and macroeconomic feedbacks.	High computational efficiency; easier to calibrate and solve compared to model coupling.	Theoretically rigorous; ensures internal consistency and equilibrium without iteration errors.
Disadvantages	Requires extensive data harmonization; computationally expensive due to iteration; potential convergence difficulties.	Loss of technological nuance; reduced form functions may fail to capture non-linearities in deep decarbonization scenarios.	Computational complexity limits sectoral granularity; often requires simplifying assumptions to remain solvable.
Recent trends	Algorithms to improve convergence speed ^[2] ; one-way or soft-link variants to reduce computational burden ^[23] .	Using machine learning or artificial intelligence (AI) methods to mimic complex models, embedding them within macro models ^[24] .	Hard-linking integration to reduce complexity and improve numerical performance ^[25] .
Typical Application	Energy transition analysis combining technology pathways and economy-wide impacts. Models include MESSAGE-MACRO ^[26] and PRIMES-GEM-E3 ^[27] .	Widely used in global integrated assessment models (IAMs) and long-term climate scenario analysis. Models include WITCH ^[28] and MERGE ^[29] .	Typically used to assess key sectoral decarbonization policies while capturing economy-wide price and welfare feedbacks. Models include MIT EPPA Model ^[30] and U.S. Electricity-Economy Model ^[31] .

modeling approach. The MCP formulation enforces market clearing and technological constraints in a single mathematical structure. Nonetheless, full integration entails substantial reconciliation between engineering databases and national accounts and can become challenging in numerical solution as each binding constraint introduces an associated dual price. Reduced-form approaches deliver internal consistency within one optimization framework but may obscure or attenuate economy-wide feedbacks when macro relationships are highly aggregated. By contrast, model coupling leverages mature domain models and remains operationally tractable for policy scenario design, provided there are explicit and documented exchange protocols and harmonized accounting across models.

Achieving carbon neutrality entails profound structural change in the world's energy systems, with annual investment on the order of trillions of US dollars and a reallocation toward clean energy and electricity infrastructure^[32]. Such shifts in both the composition and the scale of investment have substantial macroeconomic implications, making it inadequate to rely on either CGE or bottom-up models alone for policy design under a deep decarbonization transition. Yet existing modeling of China's low-carbon transition has mainly used one family or the other; few studies implement a hybrid framework to examine carbon-neutrality pathways^[33,34]. We address this gap by developing a coupled energy–environment–economy framework for China's greenhouse-gas (GHG) mitigation, linking the bottom-up China-MORE (China Multi-gas Optimal Reduction Evaluation) with the top-down IMACLIM-CHN (Impact Assessment of Climate Policies Model of China). The linkage iteratively exchanges prices, energy-service demands, activity levels, and abatement costs under harmonized sectoral and accounting definitions until convergence. This design preserves technological granularity while capturing economy-wide feedbacks and policy-relevant distortions. Additionally, we extend gas coverage from CO₂ to all major GHGs—CH₄, N₂O, and fluorinated gases (F-gases)—enabling a comparison between CO₂-neutrality and GHG-neutrality pathways.

The remainder of the paper is organized as follows. Section 2 details the models and the coupling strategy. Section 3 presents a case study assessing the energy and economic impacts of China's carbon-neutrality targets. Section 4 concludes by summarizing the

advantages, applications, and potential extensions of the IMACLIM–China-MORE hybrid framework.

2 Modeling framework

2.1 Overview

The IMACLIM–China-MORE hybrid model links the bottom-up energy-system optimization model China-MORE 2.0 and the top-down CGE model IMACLIM-CHN. This section summarizes each model and the coupling approach. By combining detailed representations of energy-system optimization with macroeconomic feedbacks, the hybrid framework enables an assessment of how alternative climate targets, ranging from CO₂ neutrality to full GHG neutrality, translate into distinct energy-system transition pathways and economy-wide responses.

China-MORE 2.0 is an energy system optimization model built on the TIMES-VEDA 2.0 (The Integrated MARKAL–EFOM System and VErSatile Data Analyst) platform developed by the IEA-ETSAP (International Energy Agency Energy Technology Systems Analysis Program) project team^[35–37]. It adopts a dynamic linear-programming structure to simulate China's long-term low-carbon transition, providing quantitative projections of energy system evolution, GHG trajectories, and associated mitigation costs. Building on the original China-MORE model developed at Tsinghua University^[38], the updated version improves technological resolution and cross-module data consistency, thereby enhancing transparency and policy relevance. Key updates include: (i) Base-year recalibration. The entire system is recalibrated to 2020 using the latest official statistics to ensure consistency and data accuracy. (ii) Expanded mitigation options. The technology database now covers critical neutrality options—such as carbon capture and storage (CCS), hydrogen-based steelmaking, electric-arc furnaces, and new-energy vehicles—with techno-economic parameters updated from recent literature and expert elicitation. (iii) Enhanced power-system detail. Renewable intermittency and storage needs are captured with 24 representative time slices (six per day across four seasons) to capture operational dynamics under high shares of wind and solar. (iv) An upgraded non-CO₂ module. Emission mechanisms

are refined, the mitigation portfolio is expanded, and the multi-gas optimization is strengthened to treat CH₄, N₂O, and F-gases alongside CO₂.

IMACLIM-CHN is a single-region, 18-sector, recursive-dynamic CGE model for China, grounded in the IMACLIM-S (Integrated Model of the Economy–Climate System (Static version)) framework developed at CIRED (Centre International de Recherche sur l'Environnement et le Développement)^[39]. It ensures simultaneous consistency between physical flows, prices, and monetary accounts, and is designed to analyze medium- to long-term macroeconomic and social impacts of energy and climate policies. IMACLIM-CHN captures economy-wide interactions and policy feedbacks. However, technological substitution is represented through Constant Elasticity of Substitution (CES) functions, which provide only an abstract depiction of energy technologies and do not explicitly enforce physical system constraints. A distinctive feature is its capacity to interface with detailed bottom-up information on energy supply and end-use processes, preserving technical realism when simulating energy-system change and major technological innovations. Coupling with China-MORE 2.0 enables exploration of pathways to climate goals from the dual perspectives of technological development and economic transformation, while providing a comprehensive assessment of economy-wide policy impacts.

2.2 China-MORE 2.0

2.2.1 Model architecture and sectoral modules

As shown in Figure 1, the model comprises three main components: a core energy system optimization module, an external scenario and energy-demand projection module, and a dedicated GHG emissions module. The detailed structure of the model can be found in Figure S1 in the Electronic supplementary material (ESM). In the coupled model, the data for the energy-demand projection module is derived from the outputs of the macroeconomic model IMACLIM-CHN.

The core optimization module represents the entire energy chain—covering primary energy supply, energy conversion processes, and final energy consumption. It is formulated as a dynamic linear-programming problem that minimizes total system cost over the modeling horizon, subject to technical, resource, and policy constraints. In this module, the energy-supply component simulates domestic resource extraction using region-specific supply curves for coal, oil, gas, nuclear, and renewables, while imports are represented through differentiated cost curves by source region. The energy-conversion component includes key intermediate processes such as coal washing, coking, oil refining, and electricity and heat generation. Final energy consumption is captured across industry, transport, and buildings, each modeled with sector-specific activity and technology structures.

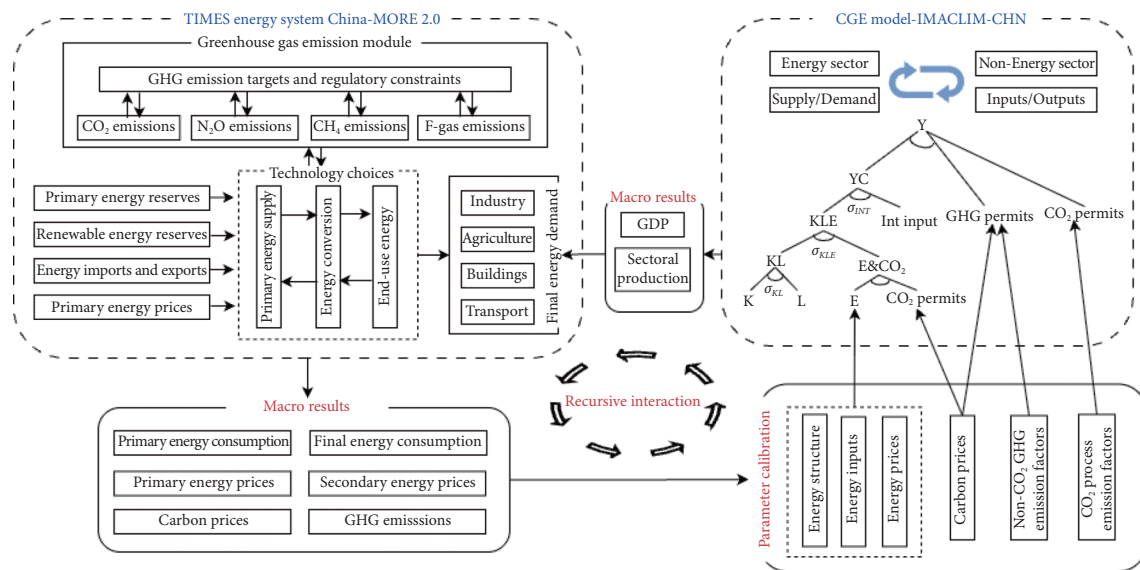


Fig. 1 Integrated modeling framework linking the TIMES-based China-MORE 2.0 energy system model with the CGE model IMACLIM-CHN.

The energy demand module relies on externally projected energy-service demands estimated using socio-economic assumptions and sector-specific methods. Within the hybrid model, future changes in industrial, transport, building, and agricultural activity are driven by sectoral output trajectories simulated by IMACLIM-CHN, ensuring consistency between economic development and energy-system evolution.

An important feature of China-MORE 2.0 is the explicit representation of non-CO₂ greenhouse gas emissions and mitigation options. The GHG emissions module quantifies CO₂, CH₄, N₂O, and F-gases from both energy and non-energy sectors. Tables S7–S9 in the ESM summarize sectoral modeling details and mitigation options for CH₄, N₂O, and F-gases. Integrated with a comprehensive mitigation-technology database, this module

consistently evaluates reduction potentials and costs across sectors. The calculated emissions feed into the core optimization module, which imposes environmental constraints that guide mitigation technology deployment and pathway selection. In this way, least-cost mitigation choices and the analysis of synergies and trade-offs among gases are determined within the system-wide optimization framework. A comprehensive description of model assumptions and detailed techno-economic parameters for all technologies is provided in the ESM (Section S2, Tables S4–S9, Figures S1–S3).

2.2.2 Mathematical formulation of the optimization model

China-MORE 2.0 is formalized as a finite-horizon, time-sliced linear programming model defined over regions, periods, technologies, commodities, and intra-period time slices. The

model minimizes discounted total system cost net of terminal salvage value, subject to a cohesive set of technical, resource, and environmental constraints. Decision variables cover capacity vintages and stocks, technology activities, and commodity flows (including storage and trade), ensuring physical and accounting consistency (Tables S1–S2 in the ESM). The constraint system enforces capacity dynamics, activity–flow linkages, operability limits by time slice, diffusion and ramp-up bounds, multi-stream process balances, commodity mass/energy balances, and pollutant accounting with policy caps; the associated dual variables admit standard economic interpretations (e.g., shadow prices for binding constraints).

The objective function of China-MORE 2.0 minimizes the present value of total system cost over the planning horizon, net of a terminal-year salvage value.

$$\min OBJ = \sum_{y \in \text{YEARS}} \frac{ANNCOST(r, y)}{(1 + d_{r,y})^{y - \text{REFYR}}} - SALVAGE(z) \quad (1)$$

Here $ANNCOST(r, y)$ denotes the total annual system cost in region r and year y , $d_{r,y}$ is the discount rate (fixed at 0.05), and $SALVAGE(z)$ represents the residual value of capital stock in the terminal year z . The annual cost includes capital investment, operation and maintenance, taxes and subsidies, decommissioning, and other lifecycle components.

$$\begin{aligned} ANNCOST(y) = & INVCOST(y) + INVTAXSUB(y) \\ & + INVDECOM(y) + FIXCOST(y) \\ & + FIXTAXSUB(y) + SURVCOST(y) \\ & + VARCOST(y) + VARTAXSUB(y) \\ & - LATEREVENUES(y) \end{aligned} \quad (2)$$

As shown in Eq. (2), the annual total system cost ($ANNCOST$) includes the investment cost ($INVCOST$), investment taxes and subsidies ($INVTAXSUB$), decommissioning cost of facilities ($INVDECOM$), annual fixed operation and maintenance cost related to installed capacity or production ($FIXCOST$), annual capacity- or production-related taxes and subsidies ($FIXTAXSUB$), variable operating cost associated with output ($VARCOST$), output-related taxes or subsidies ($VARTAXSUB$), and revenues from decommissioned facilities ($LATEREVENUES$).

The model’s decision variables include new capacity additions (VAR_{NAP}), existing capacity (VAR_{CAP}), technology activity levels (VAR_{ACT}), and commodity flows (VAR_{FLO}), among others (Tables S1–S2). These are constrained by system-level relationships that ensure technical and physical feasibility. These constraints define how the energy system can expand, operate, and supply demand over time. They track the evolution of installed capacity, link technology operation to energy and material flows, and limit utilization and expansion rates to reflect operational conditions and transition inertia. The model further represents production processes and ensures consistent balancing of energy, materials, and emissions across the system, while requiring sufficient capacity to meet peak demand. Additional constraints are used to control resource use, production levels, and emissions, and to impose policy targets such as emission caps. Together, these constraints ensure that the optimized transition pathways are technically feasible, physically consistent, and aligned with resource and environmental limits. The mathematical formulations of all constraint equations are provided in Section S1 in the ESM for completeness.

2.3 IMACLIM-CHN

The IMACLIM-CHN model uses 2020 as the base year and has a calculation step length of five years, simulating China’s energy-economic development trajectory from 2020 to 2100. It divides China’s economy into six energy sectors and twelve non-energy sectors (Table S3 in the ESM). The following subsections provide a detailed description of the key model elements, while the data foundation and computational implementation are documented in the ESM (Sections S3–S4, Table S10).

2.3.1 Production

A multi-layer nested structure represents the input–output relationships in each sector. Total output is produced from labor, capital, energy, and intermediate inputs. In addition to these conventional factors, the model incorporates emission allowance for CO₂ and non-CO₂ gases into the production nest, enabling explicit analysis of GHG-mitigation constraints. The sectoral production nests are shown in Figure 1. Given the production structure and cost-minimization behavior, factor demands are derived for each input.

In each production sector, labor L and capital K are the basic inputs. They are combined through a CES function to produce value-added KL_i , as shown in Eq. (3).

$$KL_i = (\alpha_{KL_i} K_i^{\rho_{KL_i}} + \beta_{KL_i} (\phi L_i)^{\rho_{KL_i}})^{\frac{1}{\rho_{KL_i}}} \quad (3)$$

It is assumed that capital productivity is fixed, while labor productivity rises over time with improvements in population quality and education. Therefore, a labor productivity adjustment factor ϕ is introduced in the model to adjust and calibrate future economic growth trajectories.

At the next level, sectoral value-added KL_i is combined with energy input E_i through a CES function with substitution elasticity of σ_{KLE_i} (Eq. (4)). In the CES function, ρ denotes the CES substitution parameter, which is related to the substitution elasticity by $\sigma = 1/(1-\rho)$. The quantities of energy demanded by each sector are provided exogenously by the bottom-up model China-MORE 2.0. An energy-efficiency adjustment factor ϕ_{E_i} is introduced to reflect anticipated improvements in sectoral energy efficiency. For non-energy sectors, the parameters α_{KLE_i} and β_{KLE_i} in Eq. (4) are estimated and validated from the base-year hybrid SAM (Social Accounting Matrix); for energy sectors, these parameters are updated annually using recalibrated data from China-MORE 2.0.

$$KLE_i = (\alpha_{KLE_i} KL_i^{\rho_{KLE_i}} + \beta_{KLE_i} (\phi_{E_i} E_i)^{\rho_{KLE_i}})^{\frac{1}{\rho_{KLE_i}}} \quad (4)$$

Moving up to the higher layer (Eq. (5)), KLE_i is aggregated with intermediate inputs INT_{ji} from non-energy sectors to form the conventional output YC_i of each sector using a fixed substitution elasticity σ_{YC_i} . This represents the output of each sector excluding the emission allowance for non-carbon dioxide greenhouse gases and industrial process carbon dioxide emissions.

$$YC_i = (\alpha_{YC_i} KLE_i^{\rho_{YC_i}} + \sum_j (\beta_{YC_i} INT_{ji}^{\rho_{YC_i}}))^{\frac{1}{\rho_{YC_i}}} \quad (5)$$

At the top of the nest, the conventional output is combined Leontief-wise with emission allowance for non-CO₂ and process CO₂ to yield final sectoral output Y_i (Eq. (6)). The process CO₂ emission factor $proCO_{2i}$ and the non-CO₂ emission factor nCO_{2i} are provided by China-MORE 2.0. The latter reflects CO₂-

equivalent emissions (CH₄, N₂O, F-gases, etc.) converted using GWP-100 values.

$$Y_i = \min \left\{ Y_{C_i}, \frac{nCO_{2i}}{efnCO_{2i}}, \frac{proCO_{2i}}{efproCO_{2i}} \right\} \quad (6)$$

The aggregated energy input E_i is a Leontief aggregation of carbon-emitting energy bundles $EP_{j,i}$. As in Eq. (7), the annual share $\alpha_{1,i}^E$ for each type of energy in each sector is calibrated and verified against technology model China-MORE 2.0.

$$E_i = \min_j \left\{ \frac{EP_{1,i}}{\alpha_{1,i}^E}, \frac{EP_{2,i}}{\alpha_{2,i}^E}, \dots, \frac{EP_{j,i}}{\alpha_{j,i}^E} \right\} \quad (7)$$

Each $EP_{j,i}$ is itself a Leontief bundle of physical energy consumption $EC_{j,i}$ and the associated CO₂ emission rights $CO_{2j,i}$, linked via energy and sectoral specific emission factors $efCO_{2j,i}$, supplied by China-MORE 2.0 (Eq. (8)).

$$EP_{j,i} = \min \left\{ EC_{j,i}, \frac{CO_{2j,i}}{efCO_{2j,i}} \right\} \quad (8)$$

While many carriers share common emission factors across sectors, some fuels serve as feedstocks in particular industries; China-MORE 2.0 thus provides sector-specific $efCO_{2j,i}$ where process pathways differ, improving the accuracy of emissions representation.

2.3.2 Consumption and investment

Final consumption comprises household and government consumption. The government consumption-to-GDP ratio s_G is exogenously specified. The 2020 values are calibrated to observed data, and from 2020 onward the ratio is held constant (Eq. (9)).

$$p_G G = s_G GDP \quad (9)$$

The SAM indicates that government consumption excludes energy products. Non-energy goods G , consumed by government are aggregated into the composite government consumption G using a Cobb-Douglas utility function (Eq. (10)).

$$G = \prod_i G_i^{\gamma_{G_i}} \quad (10)$$

The investment-to-GDP ratio s_I is also exogenously specified and calibrated to be consistent with potential long-run growth (Eq. (11)). The investment path is validated against capital-accumulation needs implied by economic growth trajectories (details in Section 2.3.5 Dynamic process).

$$p_I I = s_I GDP \quad (11)$$

Investment demand draws only on non-energy commodities, which are combined into total investment I via a Cobb-Douglas aggregator as shown in Eq. (12).

$$I = \prod_i I_i^{\gamma_{I_i}} \quad (12)$$

As shown in Eq. (13), households maximize utility subject to their budget using a linear-expenditure system (LES) for non-energy goods and a Leontief energy bundle, so that total consumption includes both energy and non-energy items.

$$\text{utility} = \prod_{i \in Q} (C_{Q_i} - \theta_i)^{\gamma_i^C} + \min \left\{ \frac{C_{E_i}}{\alpha_1^{CE}}, \frac{C_{E_2}}{\alpha_2^{CE}}, \dots, \frac{C_{E_i}}{\alpha_i^{CE}} \right\} \quad (13)$$

The vector of household energy consumptions C_{E_i} is provided by China-MORE 2.0, which supplies detailed uses, technologies, categories, and drivers for household energy demand. After meeting energy needs and subsistence requirements θ_i , the residual budget is allocated to non-energy goods; reductions in energy expenditure raise the budget available for non-energy consumption.

GDP is then calculated using the expenditure approach in Eq. (14).

$$\begin{aligned} GDP = & \sum_{i \in E} (C_{E_i} p_{C_{E_i}}) + \sum_{i \in Q} (C_{Q_i} p_{C_{Q_i}}) + p_G G + p_I I \\ & + \sum_{i \in E} (X_{E_i} p_{X_{E_i}}) + \sum_{i \in Q} (X_{Q_i} p_{X_{Q_i}}) - \sum_{i \in E} (M_{E_i} p_{M_{E_i}}) \\ & - \sum_{i \in Q} (M_{Q_i} p_{M_{Q_i}}) \end{aligned} \quad (14)$$

2.3.3 International trade

The import and export of energy are determined by the China-MORE 2.0 model, while imports of non-energy commodities follow the Armington assumption^[60]: domestically produced and foreign goods within the same sector are imperfect substitutes with substitution elasticity σ_{s_i} .

As shown in Eq. (15), the supply of domestic non-energy goods S_{Q_i} is a CES aggregation of domestic production Y_{Q_i} and imports M_{Q_i} .

$$S_{Q_i} = (\alpha_{s_i} Y_{Q_i}^{\rho_{s_i}} + \beta_{s_i} M_{Q_i}^{\rho_{s_i}})^{\frac{1}{\rho_{s_i}}} \quad (15)$$

The supply of energy commodities S_{E_i} is modeled as a perfect substitution between domestic production Y_{E_i} and imports M_{E_i} (Eq. (16)), and the quantity of energy imports is taken directly from China-MORE 2.0 model.

$$S_{E_i} = Y_{E_i} + M_{E_i} \quad (16)$$

Because the single-region model does not endogenize foreign demand, the composition of external demand for Chinese goods is specified exogenously. All non-energy products are aggregated via a Cobb-Douglas function into the total non-energy export composite X_Q (Eq. (17)). Base-year export shares γ_{X_i} come from the SAM, and their future paths are set exogenously to reflect assumed structural adjustments.

$$X_Q = \prod_{i \in Q} X_{Q_i}^{\gamma_{X_i}} \quad (17)$$

Import of each commodity require foreign exchange FX_{M_i} at price A_{M_i} . For energy commodities (Eq. (18)), A_{M_i} is provided by China-MORE2.0, while for non-energy commodities, A_{M_i} is held at its base-year level.

$$FX_{M_i} = A_{M_i} M_i \quad (18)$$

Exports earn foreign exchange FX_X . Energy export prices are provided by China-MORE 2.0, while the non-energy export price is fixed at its base year level (Eq. (19)).

$$FX_X = \sum_{i \in E} A_{X_i} X_{E_i} + A_{X_Q} X_Q \quad (19)$$

As an open economy, China's trade surplus B is defined as foreign-exchange earnings from exports minus foreign-exchange payments for imports (Eq. (20)). The base year value of trade surplus B is calibrated from the SAM table, and its future trajectory is set exogenously.

$$B = FX_X - \sum_{i \in E, Q} FX_{M_i} \quad (20)$$

2.3.4 Market clearing and model closure

The model adopts a Johansen-style (neoclassical) closure: labor and capital are fully employed, and their factor prices are determined endogenously. Unlike a standard neoclassical closure, this specification treats investment as exogenous and lets savings adjust endogenously to finance that investment—an assumption consistent with China's planning-oriented context. All commodity markets clear, so aggregate supply equals aggregate demand for every energy and non-energy good; factor markets also clear, with the sum of sectoral labor demands equal to the total labor endowment and aggregate capital demand equal to the capital endowment.

2.3.5 Dynamic process

The above describes the static structure of IMACLIM-CHN; intertemporal dynamics are introduced through a standard recursive mechanism, as in most CGE models. In each period, representative producers and consumers make decisions based on current prices and quantities; these choices—most notably capital accumulation—carry forward and shape subsequent periods.

The principal dynamic channel is the depreciation–accumulation process for capital. Capital evolves according to Eq. (21).

$$K_{y+1} = (1 - \delta)K_y + I_y \quad (21)$$

Where δ is the depreciation rate and I_y is the gross investment in year y . The base year capital stock K_0 is calibrated using a simple perpetuity-style rule as shown in Eq. (22).

$$K_0 = I_0 \frac{1}{\delta + g_1} \quad (22)$$

Assuming the base year capital accumulation rate equals the base year GDP growth rate g_1 , so that I_0 covers both depreciation and net additions to the capital stock.

Consistent with the Johansen-style closure used in this study, investment is specified exogenously and its path is calibrated to the assumed growth trajectory. Investment follows the identity in Eq. (23), which links the investment share of GDP $s_{i,y}$ to the target growth path (base-year share $s_{i,0}$ and growth rate g_y):

$$s_{i,y} = s_{i,0} \left[\frac{1 + g_{y+1}}{1 + g_y} - (1 - \delta) \right] \frac{K_0}{I_0} \quad (23)$$

interpreting the rule as aligning the aggregate capital-accumulation rate with GDP growth, and—purely for tractability—ignoring small differences between the future paths of the GDP deflator and the investment price index.

2.4 Model coupling

To integrate detailed technological dynamics with macroeconomic processes, we develop an iterative coupling framework linking IMACLIM-CHN and China-MORE 2.0. As illustrated in Figure 1, the iteration starts with IMACLIM-CHN simulating China's long-term economic evolution under given socio-economic scenarios. Resulting GDP and sectoral output trajectories are converted by a linking module into sector-level energy service demands, which then serve as inputs to China-MORE 2.0. The energy model optimizes the least-cost pathways to meet these demands under energy and climate policy constraints, producing detailed trajectories for energy supply, technology deployment, fuel mix, carbon prices, and emissions.

These outputs from China-MORE 2.0, such as updated energy prices, emission factors, and technological compositions, are then passed back to IMACLIM-CHN, which revises production costs, relative prices, and the macroeconomic equilibrium accordingly. The linking module updates energy-service demands based on the new macro-outcomes, and the process iterates until all exchanged variables converge within a tight tolerance (relative change $< 1 \times 10^{-4}$), delivering mutually consistent economic and energy-system trajectories.

This iterative coupling replaces the simplified energy-input assumptions in the CGE framework with China-MORE 2.0's rich technological detail while simultaneously incorporating macroeconomic feedbacks into the energy model. The approach thus bridges top-down economic projections and bottom-up technological transformation. The following subsections detail the two-way data flow: Section 2.4.1 explains how macro-outputs inform China-MORE 2.0 energy demands, and Section 2.4.2 describes how energy-system results update IMACLIM-CHN parameters.

2.4.1 IMACLIM-CHN to China-MORE 2.0 linkage

IMACLIM-CHN generates macro indicators—principally GDP and sectoral output—that the linking module converts into sector-specific energy-service demands (Table 2). Sectoral characteristics are treated with tailored methods: industrial demands scale with physical output to capture structural change; transport separates private vehicle use (modeled via a Gompertz function of per-capita GDP) from other transport services that scale elastically with sector activity^[41]; building energy demand derives from per-capita floor space and appliance ownership modeled with S-shaped income response curves; agricultural energy use follows sector output, while non-CO₂-relevant product demands are projected with GDP-dependent consumption curves. Detailed formulas and calibration procedures are provided in Section S5 in the ESM.

2.4.2 China-MORE 2.0 to IMACLIM-CHN linkage

The linking module aggregates process-level outputs from China-MORE 2.0 into sectoral parameters compatible with IMACLIM-CHN. Each year, it calibrates energy-sector production functions, non-energy sector energy-use patterns, energy prices, emission factors, and carbon-price trajectories (Table 3). Consistent production- and consumption-side mappings maintain coherence across models. Energy prices from China-MORE 2.0 serve as benchmarks for calibrating endogenous prices in IMACLIM-CHN (under constant base-year real prices). Emission factors—fuel-combustion CO₂, process CO₂, and non-CO₂ gases—are updated dynamically to reflect evolving technology mixes. Carbon prices obtained from China-MORE 2.0's cost-minimizing solutions are imposed as fixed trajectories in IMACLIM-CHN to harmonize climate-policy representation. Convergence of the iteration ensures a stable and internally consistent coupling. Mathematical details and calibration steps are provided in Section S5 in the ESM.

3 An illustrative example: energy and economic impacts of China's carbon neutrality target

This section illustrates the application of the IMACLIM–China-MORE 2.0 hybrid model to assess the energy and economic implications of China's carbon-neutrality pathways. The exercise

Table 2 Outputs from IMACLIM-CHN and corresponding parameters affected in China-MORE 2.0.

IMACLIM-CHN output	Affected parameters in China-MORE 2.0
GDP	Per capita building floor area
GDP	Per capita useful energy demand for cooking and water heating
GDP	Average household ownership of various appliances
GDP	Per capita demand for meat, eggs, dairy, grains, and vegetables
GDP	Per capita private vehicle travel demand
Output of the transport sector	Passenger and freight transport service demand
Output of the agriculture, forestry, animal husbandry, and fishery sectors	Final energy demand of the agriculture sector
Output of the food, beverage, and tobacco sectors	Product output demand in food, beverage, and tobacco processing
Output of the chemical sector	Demand for caustic soda, soda ash, ammonia, ethylene, calcium carbide, rubber, plastics, and other chemical products
Output of the steel sector	Steel production demand
Output of the non-ferrous metals sector	Production demand for aluminum, copper, lead, zinc, and other metals
Output of the non-metallic materials sector	Production demand for cement, lime, bricks, ceramics, and other non-metallic products
Output of the equipment manufacturing sector	Final energy demand of equipment manufacturing
Output of the construction sector	Final energy demand of the construction sector
Output of other industrial sectors	Final energy service demand in sectors such as textiles, wood processing, pulp and paper, cultural and entertainment goods, and water supply

Table 3 Outputs from the China-MORE 2.0 model and corresponding parameters affected in IMACLIM-CHN.

China-MORE 2.0 output	Affected parameters in IMACLIM-CHN
Energy input by energy sector	
Energy output by energy sector	Energy input coefficients in production functions of energy sectors; KL input coefficients; intermediate input coefficients
Energy input prices for energy sectors	
Energy output prices for energy sectors	
Energy inputs by type for non-energy sectors	Energy input coefficients for non-energy sectors
Energy prices by type for non-energy sectors	
CO ₂ emissions from fuel combustion by sector	Emission factors for CO ₂ emissions from fuel combustion by sector
CO ₂ emissions from industrial process by sector	Emission factors for CO ₂ emissions from industrial processes by sector
CH ₄ emissions by sector	Emission factors for CH ₄ emissions by sector
N ₂ O emissions by sector	Emission factors for N ₂ O emissions by sector
F-gas emissions by sector	Emission factors for F-gas emissions by sector
Energy imports	Energy import quantities
Energy exports	Energy export quantities

is designed to demonstrate the framework’s capability to link detailed technological pathways with macroeconomic analysis rather than to deliver a definitive pathway assessment. Three scenarios are compared to explore emissions trajectories, energy transitions, and macroeconomic impacts, highlighting trade-offs and synergies between climate ambition and economic development across sectors.

3.1 Scenario assumptions

This section outlines the assumptions defining three policy scenarios—Current Policies, CO₂ Neutrality, and GHG Neutrality—organized around socioeconomic pathways,

structural economic change, and energy-climate policy settings, each shaping emissions and economic outcomes in the model.

3.1.1 Socioeconomic assumptions

Socioeconomic development is a primary driver of final demand and energy use, and thus of the pace and feasibility of low-carbon transitions. The analysis adopts the SSP2 (“Middle of the Road”) pathway from the Shared Socioeconomic Pathways (SSP) framework, which assumes moderate challenges to mitigation and adaptation, with global social, economic, and technological trends broadly following historical patterns^[42–44]. SSP2 underpins many global and regional climate assessments, including the

Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC AR6).

The SSP2 trajectory is calibrated to China's observed population, GDP, and urbanization over 2015–2020, with post-2020 projections following the original SSP2 trends. Under this pathway, population peaks near 1.42 billion in the near term before declining to around 1.2 billion by 2060 and around 0.79 billion by 2100. GDP grows rapidly through mid-century, reaching 3.6 times the 2015 level by 2060 and then slowing under demographic headwinds. Per-capita GDP rises to 106,000 CNY in 2030, 207,000 CNY in 2060, and 337,000 CNY in 2100. The urbanization rate increases to 77% by 2060 and 82% by 2100. Although the socioeconomic scenario is calibrated using Chinese statistic data and serves as the most probable future pathway for analysis, these macroeconomic assumptions may significantly impact baseline energy demand and emissions. Should faster economic growth materialize in the future, greater demand for energy services would increase the abatement cost. Conversely, a more rapid decline in population would help alleviate the pressure to reduce emissions.

3.1.2 Economic structural transition assumptions

The model incorporates assumptions on the evolution of China's consumption and investment structures, reflecting national development targets and trends observed in mature economies. As China reaches a moderately developed income level by 2035, its final consumption pattern is assumed to converge toward the current EU average^[49]. With continued economic growth, the share of material-intensive consumption declines: expenditure on agricultural products and food decreases due to population

decline, while construction-related consumption contracts as per capita housing space approaches saturation. In contrast, service-related consumption rises considerably, accounting for 72% of total non-energy consumption by 2035 and 80% by 2060. Notably, the consumption of energy products is not predetermined in the economic module but is endogenously determined by energy service demand and technological transformation in the energy system model.

The investment structure is expected to shift in line with China's transition from high-speed to high-quality growth. As infrastructure construction and industrialization mature, fixed asset investment gradually moves away from traditional infrastructure and manufacturing toward services and new forms of infrastructure. By 2035, the service sector's share of total investment is projected to reach 30%, rising further to 44% by 2060, supporting China's broader transition toward a more innovation-driven and service-oriented economy. The projected shift towards service-oriented consumption and investment implies a structural reduction in the energy intensity of GDP. If this transition occurs more slowly than assumed, the energy system would face a heavier burden to decarbonize the supply side to meet the same neutrality target.

3.1.3 Energy and climate policy assumptions

Building upon the socioeconomic trends and economic structural transition outlined above, this study constructs three policy scenarios reflecting different energy and climate policy assumptions: the Current Policies scenario, the CO₂ Neutrality scenario, and the GHG Neutrality scenario. The main policy settings are summarized in Table 4.

Table 4 Scenario assumptions.

Scenario	Description
Current Policies (CPS)	Includes existing CO ₂ mitigation policies (Table S11) and sectoral non-CO ₂ GHG reduction measures (Table S12). Target: Reduce CO ₂ intensity per unit of GDP by 60–65% by 2030 relative to 2015, consistent with China's 2030NDC.
CO ₂ Neutrality (CNS)	Builds on the Current Policies scenario by adding a carbon neutrality target for CO ₂ . Non-CO ₂ GHGs continue to follow existing mitigation measures without total emissions caps. Target: Achieve near-zero CO ₂ emissions by 2060 through a cumulative CO ₂ emissions constraint over 2020–2100.
GHG Neutrality (GNS)	Builds on the CO ₂ Neutrality scenario by extending the neutrality target to include all greenhouse gases. Target: Achieve near-zero total GHG emissions by 2060 through a cumulative GHG emissions constraint over 2020–2100.

The Current Policies scenario captures existing major energy and economic policies (Table S11 in the ESM) excluding the carbon neutrality target, thereby simulating the development trajectory of China's energy system and emissions under prevailing conditions. In contrast, the CO₂ Neutrality scenario is designed based on a cumulative CO₂ emissions constraint, which imposes a carbon budget to achieve near-zero CO₂ emissions by 2060. Notably, this cumulative budget is not a fixed input parameter; rather, it is treated as a variable dynamically adjusted within the model through iterative computation to precisely meet the neutrality target.

Extending the analysis beyond CO₂ emissions, this study further develops a GHG Neutrality scenario that integrates all greenhouse gases under a total emission control framework. The Current Policies and CO₂ Neutrality scenarios are enriched by coupling with the non-CO₂ greenhouse gas module of the IMACLIM-China-MORE model, enabling the simulation of major existing non-CO₂ mitigation policies (Table S12) and capturing the full greenhouse gas emission trends under each

scenario. The GHG Neutrality scenario assumes that non-CO₂ greenhouse gases are jointly included within the cumulative emissions constraint. Similar to the CO₂ Neutrality scenario, the model applies an aggregated carbon budget to realize near-zero emissions of all greenhouse gases by 2060. This scenario simulates the emission trajectories of various greenhouse gases and evaluates their combined impacts on China's energy-economic system when the neutrality goal encompasses all greenhouse gases.

3.2 Results

3.2.1 Emission pathways and energy transition under various scenarios

Under the Current Policies scenario (CPS), total GHGs (12.5 Gt CO₂-eq) and non-CO₂ GHGs (2.47 Gt CO₂-eq) both peak around 2030. Thereafter, total emissions decline to 7.5 Gt by 2060 and 7.1 Gt by 2100 (Figure 2(a)), while non-CO₂ reductions are largely incidental—arising from energy-system changes rather than targeted measures (Figure 2(b)). Under CO₂ Neutrality, stronger

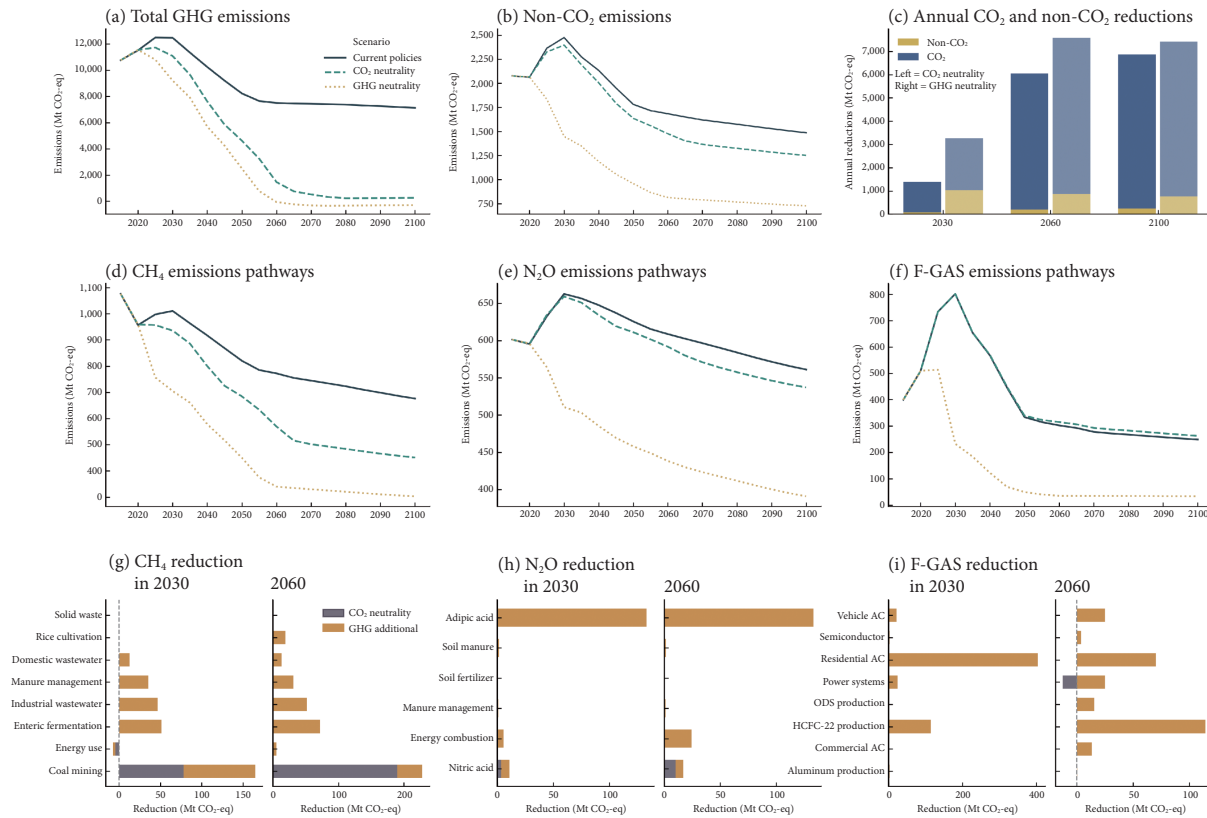


Fig. 2 Pathways and sectoral decomposition of CO₂ and non-CO₂ greenhouse gas reductions in China under CO₂ and GHG neutrality scenarios. (a–b) Historical and projected trajectories of total GHG emissions and non-CO₂ GHG emissions (CH₄, N₂O, F-GAS) under the three scenarios. (c) Annual reductions in CO₂ and non-CO₂ emissions by 2030, 2060, and 2100 under CO₂ and GHG neutrality targets. (d–f) Emission trajectories of CH₄, N₂O, and F-GAS under the three scenarios. (g–i) Source-specific CH₄, N₂O, and F-GAS reductions by (left) 2030 and (right) 2060 under CO₂ and GHG neutrality scenarios, where blue bars indicate reductions under the CO₂ neutrality scenario and red bars represent additional reductions under the GHG neutrality scenario.

CO₂ abatement delivers larger total GHG reductions—1.39 Gt (2030) and 6.05 Gt CO₂-eq (2060) relative to CPS (Figure 2(c))—but non-CO₂ gases contribute only 3%–5% of these gains, reflecting weak synergies with CO₂-focused measures (e.g., coal-mine methane, combustion-related N₂O). Even with CO₂ neutrality, cumulative non-CO₂ emissions over 2020–2100 reach 91.5 Gt CO₂-eq, a quantity comparable to roughly one-quarter of the IPCC AR6 global 1.5 °C carbon budget (400 Gt CO₂-eq)^[32]. These results highlight the need to integrate explicit non-CO₂ mitigation into long-term strategy, given diffuse sources, limited co-benefits, and persistent residuals.

Adding explicit controls on all gases unlocks additional mitigation beyond CO₂-only pathways. Under GHG Neutrality, non-CO₂ emissions fall by 40% by 2030 and 52% by 2060 versus CPS, to 1.45 Gt (2030) and 0.81 Gt CO₂-eq (2060) (Figure 2(b)). Cumulatively, non-CO₂ emissions over 2020–2100 decline by 45% to 56 Gt CO₂-eq (Figure 2(c)), substantially easing pressure on the remaining global carbon budget. Gas-specific trajectories (Figures 2(d)–2(i); Figure S4 in the ESM) further reveal pronounced heterogeneity in mitigation pathways across gases and emitting sectors.

Methane mitigation exhibits strong sectoral asymmetry, with national trends largely governed by coal mining and agricultural sources. In 2015, coal extraction, livestock enteric fermentation, and rice cultivation accounted for 43%, 20%, and 17% of total CH₄ emissions, respectively. Under CO₂ neutrality, methane reductions arise mainly as co-benefits of accelerated coal phase-

out, lowering 2060 emissions by about one quarter relative to CPS. In contrast, GHG neutrality enables a fundamentally different pathway, with CH₄ emissions declining continuously from 2020 onward and reaching about 3.4 Gt CO₂-eq by 2060—around 40% lower than under CO₂ neutrality. While coal mining dominates methane abatement through energy-system linkages, residual emissions increasingly concentrate in agriculture, where mitigation options are weakly coupled to decarbonization and constrained by biological processes, making agricultural CH₄ a persistent barrier to full GHG neutrality (Figure 2(g); Figure S5 in the ESM).

By contrast, mitigation pathways for N₂O and F-gases are shaped less by energy substitution than by technological maturity and regulatory design. Although agriculture accounted for over half of national N₂O emissions in 2015, the most cost-effective and readily deployable mitigation options lie in industrial processes—particularly adipic and nitric acid production—where mature end-of-pipe technologies enable rapid abatement once GHG controls are introduced. As a result, CO₂ neutrality delivers only limited co-benefits for N₂O, whereas GHG neutrality enables early and substantial reductions, with industrial sources contributing roughly 80%–90% of total abatement by mid-century (Figure 2(h)); agricultural N₂O, by contrast, remains highly persistent due to fertilizer demand and food security constraints.

F-gas mitigation follows a similarly policy-driven but temporally inert trajectory: despite early regulatory intervention under the Montreal Protocol and the Kigali Amendment,

emissions peak only around 2030 because refrigerant leakage occurs over long equipment lifetimes. Under GHG neutrality, accelerated deployment of low-GWP alternatives and strengthened product standards enables deep reductions by 2060, whereas CO₂-focused pathways provide little mitigation and may even induce slight increases through electrification-related uses (Figure 2(i)). Together, these patterns underscore that non-CO₂ mitigation hinges on sector-specific technologies and regulatory timing, leaving agriculture- and service-dominated emission sources as persistent sources of residual emissions beyond the reach of energy-system decarbonization.

Meeting GHG neutrality therefore imposes stricter decarbonization demands across end-use sectors (Figure 3), reflecting the limited abatement potential and persistence of residual non-CO₂ emissions. In industry, electrification rate reaches 74% by 2060 (67% under CO₂ neutrality), enabling fossil fuel substitution and increased hydrogen uptake (Figures 3(a) and 3(d)). In buildings, electrification rate reaches 90% under both scenarios, but GHG neutrality achieves this target five years

earlier, stabilizing demand sooner and nearly eliminating direct emissions (Figures 3(b) and 3(e)). Transport is more challenging: while energy demand in 2060 is similar across scenarios, GHG neutrality requires hydrogen to supply 22.8% of energy—more than twice that under CO₂ neutrality—to decarbonize freight and aviation, cutting emissions about a decade earlier (Figures 3(c) and 3(f)). Overall, GHG neutrality necessitates faster electrification, earlier hydrogen deployment, and sector-specific mitigation strategies.

These end-use transformations largely increase pressure on the power and energy supply systems. By 2060, electricity demand reaches 20,802 TWh—12% higher than under CO₂ neutrality (Figure 4(a)). To meet the climate target, coal power is fully phased out by 2040, and the renewable share rises to 90.4% (vs. 88.4%). Biomass with CCS is deployed earlier to provide dispatchable negative emissions and grid flexibility. These shifts reshape the primary energy mix: following a plateau around 2030, total primary energy use peaks at 6.9 Gtce by 2060, with fossil fuels falling to 15% and coal to just 6%—about five years ahead of the CO₂ neutrality pathway (Figure 4(b)).

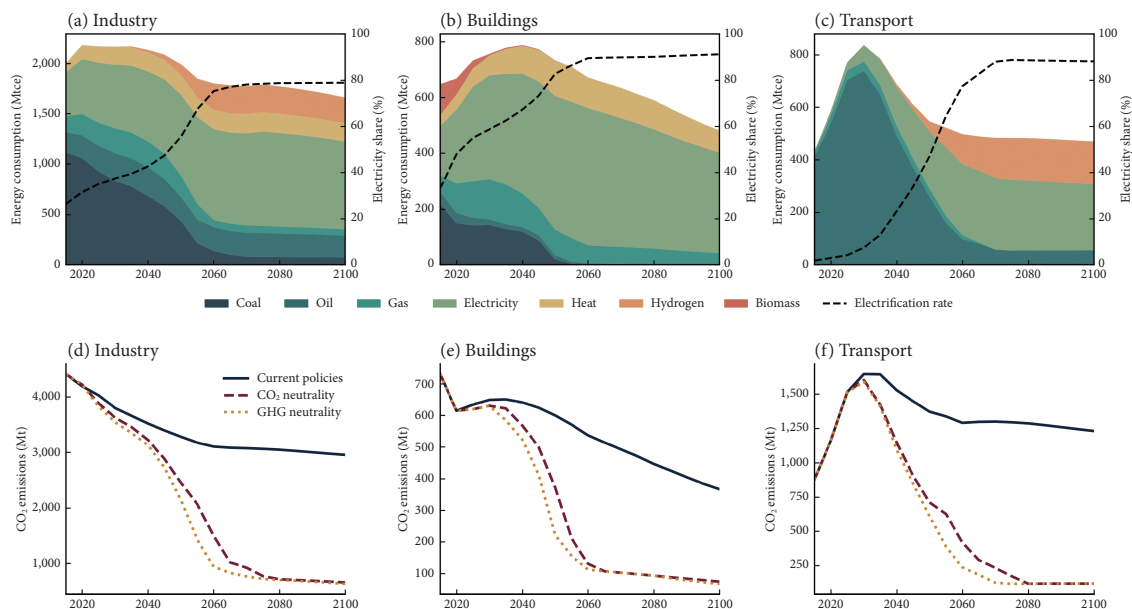


Fig. 3 Sectoral trends in energy use and CO₂ emissions under different scenarios. (a–c) Final energy consumption by fuel type and electrification rate in the industry, buildings, and transport sectors under the GHG neutrality scenario. (d–f) CO₂ emissions pathways for each sector under three scenarios.

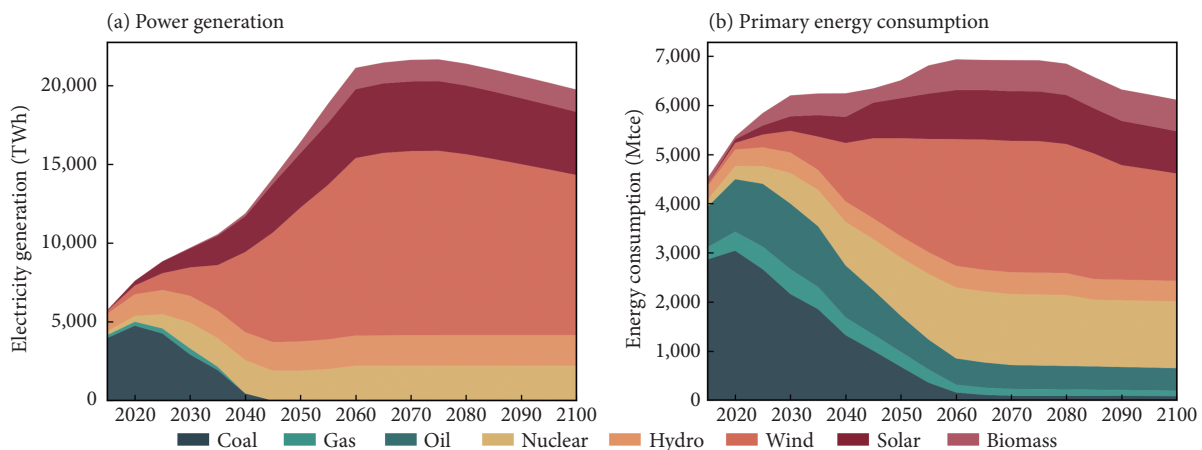


Fig. 4 Energy structure under the GHG neutrality scenario from 2015 to 2100. (a) Electricity generation mix (TWh). (b) Primary energy consumption composition (Mtce) over the same period.

3.2.2 Economic impacts and sectoral analysis

The economic cost of climate policy is a key concern for policymakers. In the hybrid model, carbon prices are adjusted to meet climate targets. As shown in Figure 5(a), prices rise sharply after 2020 due to tighter carbon quotas, reaching CNY 212/tCO₂-eq (CO₂ Neutrality) and CNY 282/tCO₂-eq (GHG Neutrality) by 2030, and escalating to CNY 917 and CNY 1,221 by 2060. These levels are lower than those projected in IPCC AR6 scenarios because traditional models have certain limitations: top-down

models often underestimate substitution potential, while bottom-up models ignore economic feedbacks like demand shifts. The coupled model addresses both, offering more accurate projections of carbon pricing and GDP impacts. Under the CO₂ Neutrality scenario, GDP losses are 0.35% in 2030 and 1.7% in 2060. For the GHG Neutrality scenario, the losses are higher—0.60% and 2.2% respectively—due to deeper and faster decarbonization (Figure 5(b)). However, from 2030 to 2050, economic losses plateau, driven by falling costs of renewable technologies, which help offset the impact of stricter carbon constraints.

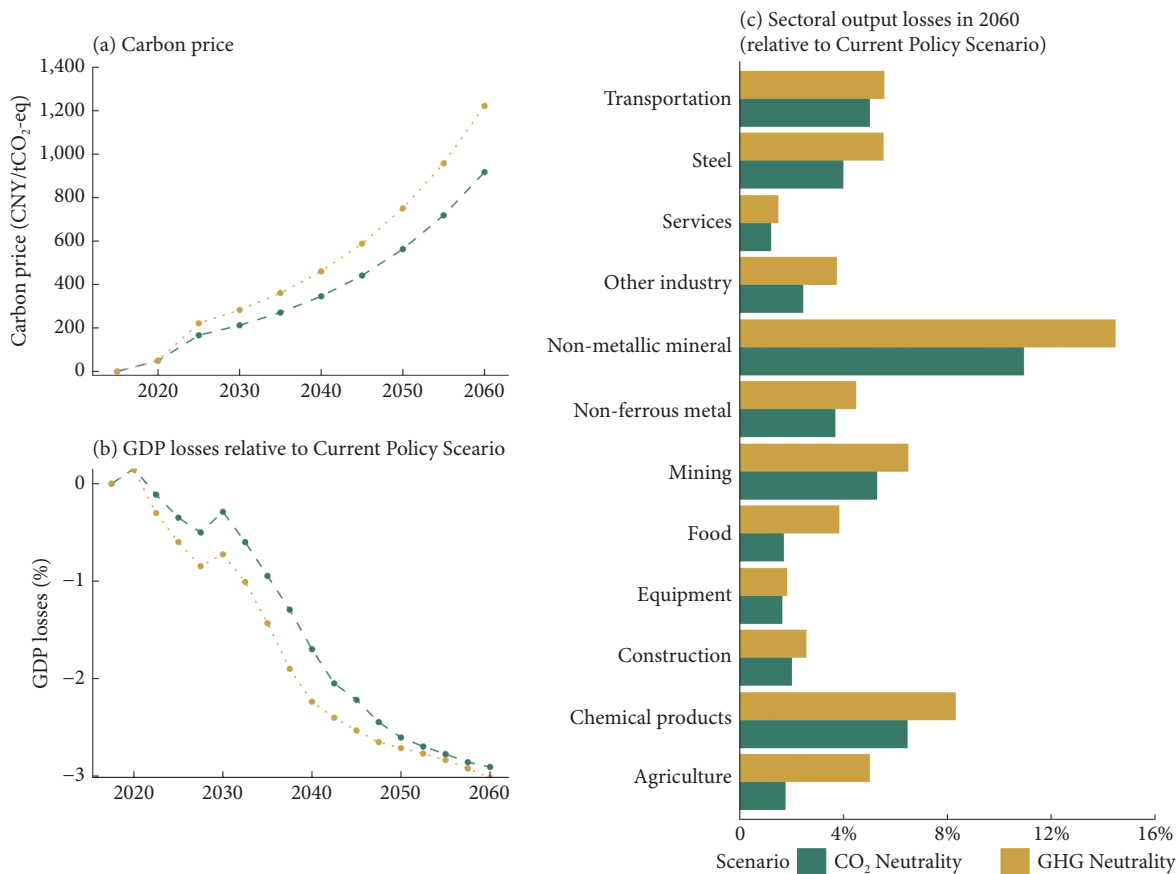


Fig. 5 (a) Carbon prices, (b) GDP losses, and (c) sectoral output losses in 2060 under CO₂ and GHG neutrality scenarios relative to CPS.

The primary source of economic cost under climate policy stems from efficiency losses in specific sectors due to carbon constraint shocks and their cumulative effects over time (Figure 5(c)). The non-metallic mineral sector faces the greatest impact, as its emissions include both energy-related and hard-to-abate process emissions, which cannot be fully mitigated even with CCS technologies. The most affected industries include the four major energy-intensive sectors, along with related mining, construction, and transportation activities. In contrast, non-energy-intensive sectors—such as equipment manufacturing, food processing, agriculture, and services—experience relatively minor impacts, typically under 3%. GHG neutrality imposes greater burdens on agriculture, food processing, and the non-metallic sector compared to CO₂ neutrality. This is largely due to the persistent challenge of reducing non-CO₂ emissions in agriculture and the downstream ripple effect on food manufacturing. Similarly, process emissions in the non-metallic sector are resistant to

reduction via energy substitution. Overall, sectoral impacts are closely tied to two factors: the technical difficulty of mitigation and the availability of effective abatement options.

Climate policy influences household consumption through its effects on income, energy use, and commodity demand patterns. While decarbonization reduces overall residential energy expenditure—partially offsetting income-related consumption declines—the impact on household consumption remains smaller than the effect on total output. By 2060, the most considerable reductions in household consumption are seen in non-metallic minerals, followed by chemicals and transportation (Figure 6(a)). Climate policy also affects fixed capital formation. Under the CO₂ Neutrality scenario, the transportation sector experiences the largest reduction in capital-related consumption, with a 5.3% decline by 2060 (Figure 6(b)). Under the more ambitious GHG Neutrality target, the agricultural sector sees an additional 3.7% drop in capital formation. In contrast, the service sector is

minimally affected. Increasing the service sector’s share in both consumption and investment could help mitigate the economic losses associated with climate policy.

Achieving carbon neutrality will require substantial financial investment. Under the CO₂ Neutrality scenario, additional annual investment needs relative to current policies are projected to reach CNY317 billion by 2030 and escalate to CNY2.179 trillion by 2060. For the GHG Neutrality pathway, incremental investment

diverges from CO₂ Neutrality after 2035, rising from CNY480 billion in 2030 to approximately CNY2.92 trillion by 2060. The bulk of this investment is concentrated in the power, transportation, hydrogen, and construction sectors (Figure 7), with the power sector alone accounting for over 70% of the total. In contrast, investment specifically targeting non-CO₂ GHG mitigation—required under the GHG Neutrality scenario—remains relatively modest, stabilizing at CNY20–30 billion annually.

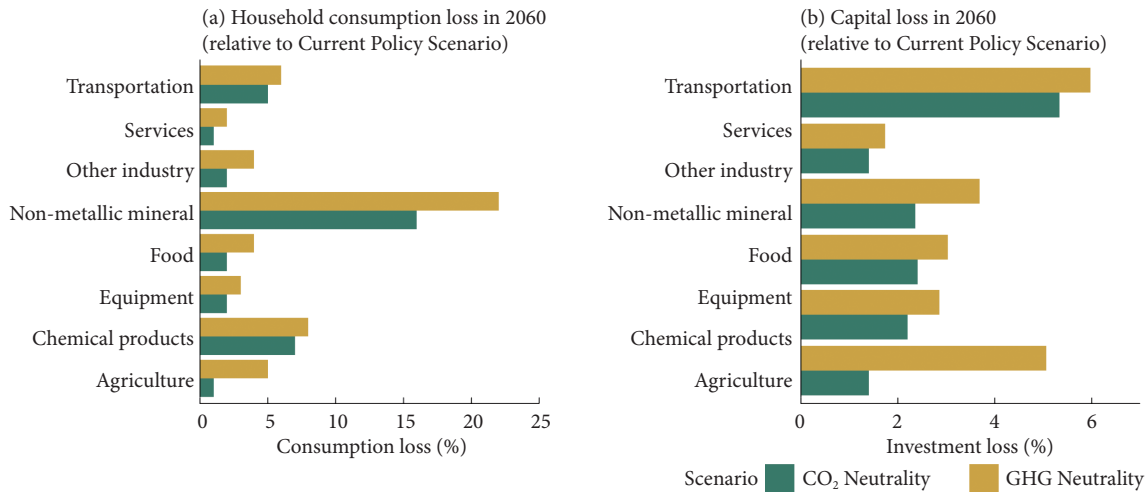


Fig. 6 Household consumption loss (a) and capital loss (b) in 2060 under CO₂ and GHG neutrality scenarios relative to CPS.

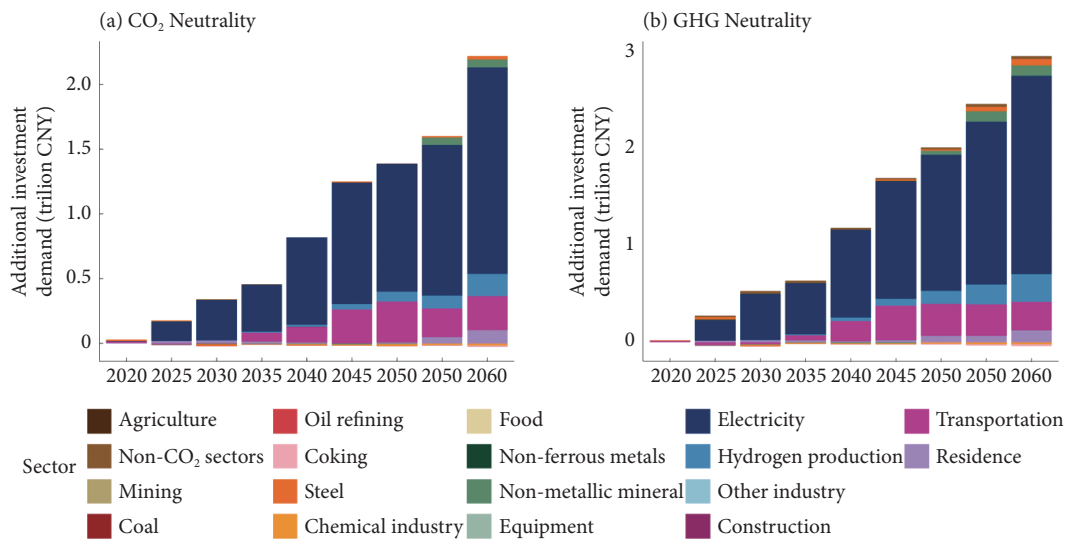


Fig. 7 Additional investment demand of 18 sectors under CO₂ and GHG neutrality scenarios relative to CPS.

4 Conclusion

This study presents the IMACLIM-China-MORE model, a coupled hybrid framework that integrates a bottom-up energy system model with a top-down CGE model to assess long-term transition pathways under China’s CO₂ and GHG neutrality targets. Beyond combining technological detail with macroeconomic consistency, the key methodological contribution of this framework lies in its ability to evaluate how changes in climate policy targets—from CO₂ neutrality to full GHG neutrality—reshape energy-system transformation and economic outcomes within a unified modeling structure.

Model applications under three scenarios demonstrate the framework’s capacity to support comprehensive policy analysis. A central insight emerging from the coupled CGE–TIMES structure is that explicitly accounting for non-CO₂ greenhouse gases fundamentally alters the system-wide requirements for achieving climate neutrality. While CO₂ neutrality can be attained primarily through energy substitution and electrification—allowing China to reach net-zero CO₂ emissions by 2060—substantial residual emissions of CH₄, N₂O, and F-gases remain, amounting to roughly 1.5 Gt CO₂-eq. When the policy target is extended to full GHG neutrality, these residual non-CO₂ emissions significantly tighten the remaining mitigation space, requiring additional

abatement equivalent to around 0.8 Gt CO₂-eq to be offset by negative-emission technologies. This shift imposes stricter and earlier decarbonization demands on CO₂-intensive sectors, accelerating electrification, hydrogen deployment, and coal phase-out. These results illustrate that non-CO₂ mitigation is not merely an add-on to CO₂ strategies, but a critical determinant of the overall transition pathway and its economic implications.

Due to its granular representation of non-CO₂ gases and associated mitigation technologies, the model is well suited for analyzing comprehensive GHG mitigation policies. However, the current CGE model aggregates the economy into 18 sectors, which limits the resolution of sectoral dynamics. Future improvements could involve refining sectoral disaggregation to better capture China's economic structure and intersectoral transmission mechanisms. Additionally, calibrating model parameters and conducting uncertainty analyses on key assumptions would enhance the robustness of the results. The socioeconomic and economic structural transition assumptions reflect our assessment of China's future development trajectory. However, the sensitivity of the model results to these macroeconomic assumptions requires further quantification, particularly when applying the model to examine specific policy issues. Beyond transition pathway modeling, the framework could be extended by integrating a climate impact module to incorporate avoided climate damages into policy assessments. This enhancement would enable a more comprehensive evaluation of the net costs and benefits of climate mitigation strategies, thereby supporting more informed decision-making for long-term climate policy in China.

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Author contribution

Fei Teng conceived and designed the study. Xin Su developed the model and conducted the analysis. Xin Su, Bowen Wang, and Ziqi Wu collected and curated the data. Fei Teng, Bowen Wang, and Ziqi Wu interpreted the results and wrote the initial draft. All authors contributed to manuscript revision, read, and approved the submitted version.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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. The author Fei Teng is the Executive Editor-in Chief of this journal.

Electronic supplementary material

Supplementary material is available article in the online version of this article at <https://doi.org/10.26599/ECM.2026.9400032>.

References

- [1] Herbst, A., Toro, F., Reitze, F., Jochem, E. (2012). Introduction to energy systems modelling. *Swiss Journal of Economics and Statistics*, 148(2): 111–135.
- [2] Pisciella, P., Van Beesten, E. R., Tomagard, A. (2023). Efficient coordination of top-down and bottom-up models for energy system design: an algorithmic approach. *Energy*, 284: 129320.
- [3] Cao, J., Dai, H. C., Li, S. T., Guo, C. Y., Ho, M., Cai, W. J., He, J. W., Huang, H., Li, J. F., Liu, Y., et al. (2021). The general equilibrium impacts of carbon tax policy in China: a multi-model comparison. *Energy Economics*, 99: 105284.
- [4] Jia, Z. J., Lin, B. Q. (2022). CEEEA2.0 model: a dynamic CGE model for energy-environment-economy analysis with available data and code. *Energy Economics*, 112: 106117.
- [5] Böhringer, C., Rutherford, T. F. (2008). Combining bottom-up and top-down. *Energy Economics*, 30(2): 574–596.
- [6] Böhringer, C. (1998). The synthesis of bottom-up and top-down in energy policy modeling. *Energy Economics*, 20(3): 233–248.
- [7] Wene, C. O. (1996). Energy-economy analysis: linking the macroeconomic and systems engineering approaches. *Energy*, 21(9): 809–824.
- [8] Fujimori, S., Oshiro, K., Shiraki, H., Hasegawa, T. (2019). Energy transformation cost for the Japanese mid-century strategy. *Nature Communications*, 10(1): 4737.
- [9] Prina, M. G., Manzolini, G., Moser, D., Nastasi, B., Sparber, W. (2020). Classification and challenges of bottom-up energy system models - A review. *Renewable and Sustainable Energy Reviews*, 129: 109917.
- [10] Grubb, M., Edmonds, J., Ten Brink, P., Morrison, M. (1993). The costs of limiting fossil-fuel CO₂ emissions: a survey and analysis. *Annual Review of Environment and Resources*, 18: 397–478.
- [11] Binswanger, M. (2001). Technological progress and sustainable development: what about the rebound effect. *Ecological Economics*, 36(1): 119–132.
- [12] Krook-Riekkola, A., Berg, C., Ahlgren, E. O., Söderholm, P. (2017). Challenges in top-down and bottom-up soft-linking: lessons from linking a Swedish energy system model with a CGE model. *Energy*, 141: 803–817.
- [13] Andersen, K. S., Termansen, L. B., Gargiulo, M., Ó Gallachóir, B. P. (2019). Bridging the gap using energy services: demonstrating a novel framework for soft linking top-down and bottom-up models. *Energy*, 169: 277–293.
- [14] Hourcade, J. C., Jaccard, M., Bataille, C., Ghersi, F. (2006). Hybrid modeling: new answers to old challenges introduction to the special issue of the energy journal. *The Energy Journal*, 27(S2): 1–11.
- [15] Gupta, D., Ghersi, F., Vishwanathan, S. S., Garg, A. (2020). Macroeconomic assessment of India's development and mitigation pathways. *Climate Policy*, 20(7): 779–799.
- [16] Dai, H. C., Mischke, P., Xie, X. X., Xie, Y., Masui, T. (2016). Closing the gap? Top-down versus bottom-up projections of China's regional energy use and CO₂ emissions. *Applied Energy*, 162: 1355–1373.
- [17] Helgesen, P. I., Lind, A., Ivanova, O., Tomagard, A. (2018). Using a hybrid hard-linked model to analyze reduced climate gas emissions from transport. *Energy*, 156: 196–212.
- [18] Chen, W. Y. (2005). The costs of mitigating carbon emissions in China: findings from China MARKAL-MACRO modeling. *Energy Policy*, 33(7): 885–896.
- [19] Kyreos, S., Lehtila, A. (2015). Decomposing TIAM-MACRO to assess climatic change mitigation. *Environmental Modeling & Assessment*, 20(6): 571–581.
- [20] Weng, Y. W., Chang, S. Y., Cai, W. J., Wang, C. (2019). Exploring

- the impacts of biofuel expansion on land use change and food security based on a land explicit CGE model: a case study of China. *Applied Energy*, 236: 514–525.
- [21] Bachner, G., Lincke, D., Hinkel, J. (2022). The macroeconomic effects of adapting to high-end sea-level rise via protection and migration. *Nature Communications*, 13(1): 5705.
- [22] Cao, Z., Liu, G., Zhong, S., Dai, H. C., Pauliuk, S. (2019). Integrating dynamic material flow analysis and computable general equilibrium models for both mass and monetary balances in prospective modeling: a case for the Chinese building sector. *Environmental Science & Technology*, 53(1): 224–233.
- [23] Schreiber, A., Evans, D., Marten, A., Wolverton, A., Davis, W. (2025). Evaluating economy-wide impacts of complex regulations: a hybrid linking approach for detailed sector and CGE models. *Energy Economics*, 145: 108458.
- [24] Prina, M. G., Dallapiccola, M., Moser, D., Sparber, W. (2024). Machine learning as a surrogate model for EnergyPLAN: speeding up energy system optimization at the country level. *Energy*, 307: 132735.
- [25] Helgesen, P. I., Tomasgard, A. (2018). From linking to integration of energy system models and computational general equilibrium models – effects on equilibria and convergence. *Energy*, 159: 1218–1233.
- [26] Messner, S., Schratzenholzer, L. (2000). MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. *Energy*, 25(3), 267–282.
- [27] Capros, P., Paroussos, L., Fragkos, P., Tsani, S., Boitier, B., Wagner, F., Busch, S., Resch, G., Blesl, M., Bollen, J. (2014). Description of models and scenarios used to assess European decarbonisation pathways. *Energy Strategy Reviews*, 2(3-4): 220–230.
- [28] Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., Tavoni, M. (2006). A world induced technical change hybrid model. *The Energy Journal*, 27(S2): 13–37.
- [29] Manne, A. S., Richels, R. G. (2005). Merge: an integrated assessment model for global climate change. In: *Energy and Environment*. Loulou, R., Waub, J. P., Zaccour, G., Eds. New York: Springer, 175–189.
- [30] Paltsev, S., Reilly, J. M., Jacoby, H. D., Eckaus, R. S., McFarland, J., Sarofim, M., Asadoorian, M., Babiker, M. (2005). The MIT emissions prediction and policy analysis (EPPA) model: version 4.
- [31] Lanz, B., Rausch, S. (2011). General equilibrium, electricity generation technologies and the cost of carbon abatement: a structural sensitivity analysis. *Energy Economics*, 33(5): 1035–1047.
- [32] IPCC (2022). *Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C Above Pre-industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*. Cambridge: Cambridge University Press.
- [33] Project Team on the Strategy and Pathway for Peaked Carbon Emissions and Carbon Neutrality. (2021). Analysis of a peaked carbon emission pathway in China toward carbon neutrality. *Engineering*, 7(12): 1673–1677.
- [34] He, J. K., Li, Z., Zhang, X. L., Wang, H. L., Dong, W. J., Du, E. S., Chang, S. Y., Ou, X. M., Guo, S. Y., Tian, Z. Y., et al. (2022). Towards carbon neutrality: a study on China’s long-term low-carbon transition pathways and strategies. *Environmental Science and Ecotechnology*, 9: 100134.
- [35] Goldstein, G., Gargiulo, M., Kanudia, A. Documentation for the TIMES model. PART IV: VEDA 2.0 (IEAETSAP).
- [36] Loulou, R., Labriet, M. (2008). ETSAP-TIAM: the TIMES integrated assessment model Part I: model structure. *Computational Management Science*, 5(1): 7–40.
- [37] Loulou, R. (2008). ETSAP-TIAM: the TIMES integrated assessment model. Part II: mathematical formulation. *Computational Management Science*, 5(1): 41–66.
- [38] Wang, X., Teng, F., Yang, X., Wei, R. Q. (2017). Assessing the role of electricity storage in China’s high renewable energy penetration future. *Energy Procedia*, 105: 4084–4089.
- [39] Gheris, F. (2015). Hybrid bottom-up/top-down energy and economy outlooks: a review of IMACLIM-S experiments. *Frontiers in Environmental Science*, 3: 74.
- [40] Armington, P. S. (1969). A theory of demand for products distinguished by place of production (Une theorie de la demande de produits differencies d’apres leur origine) (Una teoria de la demanda de productos distinguiendolos segun el lugar de produccion). *Staff Papers - International Monetary Fund*, 16(1): 159.
- [41] Huo, H., Wang, M. (2012). Modeling future vehicle sales and stock in China. *Energy Policy*, 43: 17–29.
- [42] Rogelj, J., Popp, A., Calvin, K. V., Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Strefler, J., Hasegawa, T., Marangoni, G., et al. (2018). Scenarios towards limiting global mean temperature increase below 1.5 °C. *Nature Climate Change*, 8(4): 325–332.
- [43] Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O’Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., et al. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Global Environmental Change*, 42: 153–168.
- [44] Gidden, M. J., Riahi, K., Smith, S. J., Fujimori, S., Luderer, G., Kriegler, E., Van Vuuren, D. P., van Den Berg, M., Feng, L. Y., Klein, D., et al. (2019). Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. *Geoscientific Model Development*, 12(4): 1443–1475.
- [45] Eurostat. (2023). ESA supply, use and input-output tables. <https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/database>.