Methods and Models for Costing Carbon Mitigation

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Annu. Rev. Environ. Resour. 2013. 38:137–68

First published online as a Review in Advance on August 7, 2013

The *Annual Review of Environment and Resources* is online at http://environ.annualreviews.org

This article's doi:
10.1146/annurev-environ-083111-092115

Keywords

global, electricity, energy, iron and steel, top-down, bottom-up

Abstract

Using the results of more than 20 different global models with a particular emphasis on two rapidly growing large countries (China and India), this paper discusses the cost estimation methods that are used in setting up information for organizing models and to illustrate their global applicability to China, Korea, Japan, India, Indonesia, Europe, Latin America, the Middle East, Africa, and the United States. Some clear points emerge from the intermodal comparison exercise. First, no single technology can play a leading role in global emission mitigation. Second, although participation of all the regions is important, regions where future demographic and economic growth is concentrated will share a large part of this burden. Third, different technologies are important for different regions for mitigating emissions in the most cost-effective way. Fourth, if stringent climate policy targets are to be met, then emission-reduction actions need to be undertaken as soon as possible.

Contents

1. INTRODUCTION

Carbon mitigation refers to an anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases (GHGs). Emissions from energy use and the forestry sector account for the bulk of GHG emissions. Reducing the sources of emissions from energy and forestry sectors and enhancing the forestry-sector gas sinks can contribute substantially to slowing the growth of projected emissions over rest of this century.

Established in 1992, UNFCCC (United Nations Framework Convention on Climate Change) is the primary agency set up to reduce and limit the increase of GHGs. In Article 2 of its charter, UNFCCC states its ultimate goal to be the stabilization of GHG concentrations in the atmosphere at a level that will prevent dangerous anthropogenic interference with the climate system. It also focuses on costs, and in Article 3.3, it notes that policies and measures to deal with climate change should be cost-effective so as to ensure global benefits at the lowest possible costs. Ensuring cost-effectiveness has prompted the design of various models and the use of many approaches to estimate GHG emissions costs at national, regional, and global levels. The accuracy of the modeling approaches used to estimate these costs depends on several factors: for example, the covered area, time horizon, determination of baseline scenarios, modeling approaches [bottom-up versus top-down, hybrid models, integrated assessment models (IAMs), or simulation models], emissions sources, life-cycle considerations, trading potential, availability of a variety of fuels, import and export of fuels, inclusion of efficiency and renewable energy options, changes in costs and prices of commodities, discount rates, etc.

For most mitigation models, time horizons range from at least 2030 up to 2050 and beyond. Most baseline scenarios predict little or no change in emissions for the first 20–30 years. Reducing emissions to reach a temperature increase of 2°C by 2050 requires a rapid reduction in emissions beginning in this decade largely because CO_2 emissions remain in the atmosphere for 100 or more years. Cumulative emissions thus are an important element that requires rapid reductions relative to changes in capital stocks, which would require retrofitting existing technologies or switching to advanced technologies.

Typical top-down models focus on an aggregate level with usually 10 major regions in global models. Such sector-wide models do not usually account for individual technologies that can be evaluated for their efficiency potential. Bottom-up models resort to an approach that is initiated with detailed representation of individual technologies such as appliances, buildings, industrial processes, etc. These permit an assessment of efficiency improvements. In recent years, a significant amount of effort has focused on developing hybrid models that incorporate representation of individual technologies in the top-down models. Using IAMs, researchers also have multiple aims: to combine knowledge from multiple disciplines in formal integrated representations; inform policy making; structure knowledge; prioritize key uncertainties; and advance knowledge of broad system linkages and feedbacks, particularly those between socioeconomic and biophysical processes (1). These models were initiated in the 1990s and have continued to engage energy demand and supply options with other sources of GHG emissions such as deforestation and methane emissions. They may combine simplified representations of various factors including the socioeconomic determinants of GHG emissions, the atmosphere and oceans, impacts on human activities and ecosystems, as well as potential policies and responses.

Another more recent aspect of cost analysis is the estimation of life-cycle costs that cover the full costs and associated emissions not only of the manufacture of fuels and electricity, but also of products that are used in the manufacture and the disposal of used products. Such values vary significantly across different types of power plants: Most renewable plants have values lower than those of other plants. Thus, reports on these costs provide an important component for accurate estimates of total mitigation costs.

Researchers must also consider aspects associated with trading costs when deciding whether to import or export certain fuels. The use of traded products is also affected by their higher or significantly variable costs. As a result, investigators may opt for higher-cost products with low variability such as renewable energy and energy efficiency products. Costs must also be determined within approaches to capture and store GHGs. Associated pilot projects have been put in place in many countries.

Discussing these methods and models of costing carbon mitigation, this paper is organized as follows. Cost estimation methods are discussed in Section 2. Section 3 provides information about the different modeling approaches. Section 4 presents our evaluation of the regional and global results. Section 5 highlights the limitations of approaches and estimates and notes potential improvements to modeling techniques. Section 6 summarizes key conclusions.

2. COST ESTIMATION METHODS

Reducing GHGs is likely to incur costs associated with the use of more efficient technologies, energy supplies that have lower GHG concentrations, better control of deforestation and forestry-sector degradation, more efficient manufacturing, and improved use of agricultural products (also see related discussion on modeling options in Section 3). Thus, shifting away from the current or future use of related options may also increase costs. In best-case scenarios, the higher GHG-reduction costs may be offset by a larger reduction in the costs of the replaced options.

Actions taken to reduce GHG emissions or to increase carbon sinks divert resources from other uses. Assessing the costs of these actions should ideally consider the total value that a society attaches to forgone goods and services that must be eliminated as resources are diverted to climate protection. In some cases, the sum of benefits and costs will be negative, meaning that a society gains from undertaking the mitigation action. The costs of climate protection are affected by decisions on some key elements, the analytical structure, and the assumptions made. Key assumptions include the definition of the baseline, associated costs and benefits that arise in conjunction with GHG emission reduction policies, the flexibility available to find the carbon emissions of lowest cost, the possibility of no-regret options, the discount rate, the rate of autonomous technological change, whether revenue is recycled, the inclusion of life-cycle costs, and the consideration of travel costs for product trading (2).

The baseline applies to all the climate models discussed in this paper, and defining it is a key part of cost assessment. The baseline is a measure of the GHG emissions that would occur in the absence of climate change interventions. It helps researchers to determine how expensive GHG emission reduction may be. The baseline rests on key assumptions about future economic policies at the macroeconomic and sectoral levels, including structure, resource intensity, relative prices, technology choice, and the rate of technology adoption. The baseline also depends on assumptions about future development patterns in the economy, such as population growth, economic growth, and technological change.

Climate change policies may have a number of side effects on local and regional air pollution. They may also have indirect effects on issues such as transportation, agriculture, land-use practices, employment, and fuel security. These side effects are taken into account within many bottom-up models as well as IAMs. They can be negative or positive. In addition, their inclusion tends to generate higher or lower climate change mitigation costs compared with studies in which they are not included.

For a wide variety of options, and as often demonstrated in IAMs, the costs of mitigation depend on the regulatory framework adopted by national governments to reduce GHGs. The more flexibility allowed by the framework, the lower are the costs of achieving a given reduction. More flexibility and more trading partners can reduce costs, as a firm can seek the lowest-cost alternative. The opposite is expected with inflexible rules and few trading partners.

No-regrets options are by definition actions to reduce GHG emissions that have negative net costs. Net costs are negative when options generate direct or indirect benefits large enough to offset the costs to implement the options. The possibility of achieving no-regrets options implies that, in reality, people choose not to exercise some carbon-reducing options because of relative prices and preferences or that some markets and institutions do not behave perfectly. Such options are commonly utilized when assessing the benefits of scenarios that are focused on increased reduction of climate emissions. For example, compared with a baseline scenario, a faster increase in appliance standards could help achieve rapid no-regrets options.

Modelers use a technical coefficient called autonomous energy efficiency improvement (AEEI) to account for the penetration of technological change over time. The AEEI reflects the rate of change in the energy intensity [the ratio of energy to gross domestic product (GDP)], holding energy prices constant. The presumed AEEI in the energy intensity of an economy can lead to significant differences in the estimated costs of mitigation. As such, many observers view the choice of AEEI as crucial in setting the baseline by which to judge the costs of mitigation, which are inversely proportional to the AEEI: The greater an AEEI is, the lower the costs to reach any given climate target will be. Costs decrease because people adopt low-carbon technology unrelated to changes in relative prices. The use of an AEEI becomes far more important over the long term, particularly in top-down models, owing to the challenges associated with projecting improvement in technologies out to 2100. Models often use multiple scenarios to indicate the level of uncertainty in the difference in cost estimates over time.

Other issues to be considered in the assessment of mitigation policies include the marginal cost of public funds, capital costs, and side effects. These are more likely to be accounted for within bottom-up models that can focus on specific countries or states within countries. Policies such as carbon taxes or auctioned (tradable) carbon-emissions permits generate revenues that can be recycled to reduce other taxes that are likely to be distortionary. There has been considerable debate as to whether such revenue recycling may eliminate the economic costs of such mitigation policies. Whereas theoretical studies indicate that this result could occur in economies with highly inefficient tax systems, some, though not many, empirical studies obtain the no-cost result. Tax recycling reflects several complicated assumptions in the baseline and policy case regarding, for example, the structure of the tax system and the overall policy framework. Target setting and timing also affect cost estimates. Reduction targets defined as percentage reductions of future GHG emissions also create significant uncertainty about GHG emission levels.

In addition, several issues regarding technology use in developing countries and economies in transition warrant attention as critical determinants for climate change mitigation potential and related costs. These include current technological development levels, technology transfer, capacity for innovation and diffusion, barriers to efficient technology use, institutional structure, and human capacity. Several barriers due to restrictions that need to be overcome from research and development, production, design, deployment, and sales of a product contribute to a decline in the penetration rates of technologies and an increase in their costs. Sale prices can be multiple compared with production costs. Thus, models that rely on production costs may generate much lower GDP impacts of climate reduction.

Climate mitigation strategies can be produced using input-output models, macroeconomic models, computable general equilibrium models, and models based on the energy sector (see Section 3). Top-down, bottom-up, and hybrid models as well as IAMs have also been developed to provide more detail on the structure of the economy and the energy sector. Two broad classes of IAMs can be identified: policy optimization models and policy evaluation models. The appropriate use of these models depends on the subject being evaluated and the availability of data.

Until a few years ago, mitigation modeling of climate change focused on direct emissions from the use of energy from multiple fuel sources. Such assessments largely ignored the full range of environmental damages associated with variant manufacturing sources and the final disposal of technologies. Life-cycle analyses now try to compare the full range of environmental damages of any given product, technology, or service. They usually include raw material input, energy requirements, and waste and emissions production. Inclusion of such items indicates a more complete recognition of the fuels and other sources that contribute to climate emissions. As in a cradle-to-grave approach, such factors include the operation of a technology, facility, or product as well as all upstream (i.e., those occurring prior to when a technology, facility, or product is put into operation) and downstream (i.e., those occurring after the useful lifetime of a technology, facility, or product) processes.

A life-cycle analysis conducted recently in the Intergovernmental Panel on Climate Change Special Report on Renewable Energy Sources project yielded very supportive results for the use of renewable energy (3). This analysis documented the use of biopower, photovoltaic power, hydropower, concentrated solar power, geothermal energy, wind energy, ocean energy, and nuclear energy. It also included electricity generation from natural gas, oil, and coal. Results of this analysis indicated that GHG emissions from renewable energy technologies are generally considerably lower than those associated with fossil-fuel options and that, over a range of conditions, they are also lower than those from fossil-fuel options employing carbon capture and storage (CCS).

3. MODELS FOR COSTING CARBON MITIGATION

Over the past two decades, modeling approaches have evolved to address policy questions related to finding the costs of carbon mitigation or identifying choices for mitigation. A comprehensive list of models is provided in **Supplemental Appendix 1** (for all **Supplemental Material**, follow the link from the Annual Reviews home page at **http://www.annualreviews.org**). Below, we provide a short discussion helpful for understanding the table in **Supplemental**

Supplemental Material

Appendix 1 and for determining which choice of model may be most appropriate.

3.1. Modeling Approaches for Energy Systems

Energy systems currently contribute to the bulk of emissions and may continue to do so in the future (4). Thus, several modeling efforts have focused on estimating abatement costs arising from the energy sector. Accordingly, researchers have identified various factors to differentiate among energy models: (*a*) economic rationale, (*b*) level of disaggregation of decision variables, (*c*) time horizon, (*d*) geographic coverage, (*e*) applied mathematical techniques, (*f*) purpose of model, (*g*) degree of endogenization, (*h*) sectoral coverage, and (*i*) time dynamics (5–11). Hourcade and colleagues (6) have identified three broad purposes for energy models: to predict or forecast about the future trends, to explore the future, and to assess the feasibility of desirable futures.

There are broadly two approaches for estimating costs of carbon mitigation from energy systems: top-down and bottom-up models (**Figure 1**). This division, however, is not definitive: Hybrid models include features of both top-down and bottom-up models. Technologically disaggregated models, namely bottom-up models, are flow optimization or partial equilibrium representations of the energy sector. They provide a detailed technological representation and typically include no or very limited interactions with the macroeconomic system (12). By contrast, aggregated models, namely top-down models, have a macroeconomic perspective and focus mainly on the relations between the energy sector and other sectors of the economy. They represent sectoral economic activities through aggregate production functions. However, their energy-economy interactions provide limited representation of the energy system.

By uniting both top-down and bottom-up approaches, hybrid models combine the technological explicitness of bottom-up models with the economic comprehensiveness of top-down models (13). However, in hybrid modeling, both the bottom-up and top-down

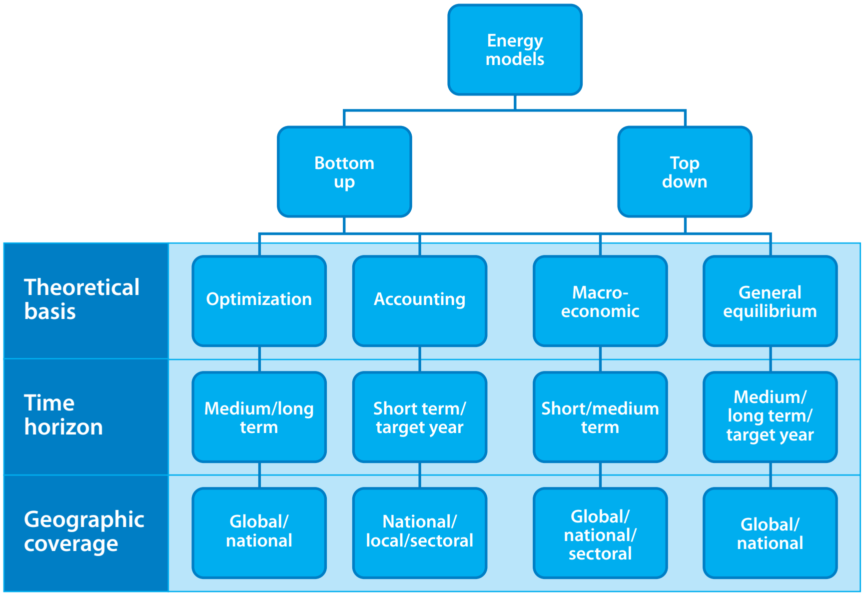


Figure 1

Modeling classification for energy models.

aspects are simplified for computational purposes (i.e., to make the model computable). Therefore, by comparison, hybrid models typically have limitations in the amount and detail of their inputs and outputs. To address some of these limitations, researchers have developed IAMs, which assess the impacts of policies to control climate change and incorporate a breadth of knowledge from multiple disciplines.

3.2. Top-Down Models

Top-down models provide a highly aggregated representation of economic and endogenization effects. They yield no or limited characterization of technologies and reflect the pessimism of economic models (7). They are, however, well suited to assess the macroeconomic impact of energy and environmental policies, especially market-oriented policies (carbon tax and tradable quota), on national and global scales (14–16). Because of limited representation, technology-related alterations such as efficiency improvements are difficult to convert explicitly into the production function of these models (6). For top-down models, the most efficient technology lies on the production frontier determined by market behavior. These models can be divided into (*a*) input-output models, (*b*) neo-Keynesian macroeconomic models, and (*c*) computable general equilibrium models (for information regarding studies of top-down models, also see **Supplemental Appendix 2**).

Input-output models are based on a system of linear equations that represent an economy as a number of industries (12). Input-output analysis shows the process by which inputs in one industry sector produce outputs for consumption or for input into another industry sector. Because macroeconomic models assume that every industry exists in an imperfect competition market, they do not calculate an equilibrium solution (6, 17). Instead, the equilibrating mechanisms of macroeconomic models work through quantity adjustments rather than price.

By contrast, general equilibrium models include all sectors of the economy and several interacting markets. The energy demand is estimated through aggregate economic indices (GDP growth, price, and price elasticities). Each sector's production output is simulated by means of a production function that allows for the substitution of a factor of production (labor, capital, energy, and material) based on the elasticity of the substitution (18). These models assume perfect market equilibrium and do not take into account structural unemployment.

These models can be static when they look at a given future year in a single step or dynamic when an entire time transition is covered in multiple time steps. In dynamic models, investments made in one period have an influence on the capital stock of the next period (17). Partial equilibrium models simplify the data requirements and can permit purposive analysis of a particular sector (e.g., the ERB model is an energy system partial equilibrium model) (19).

General equilibrium models traditionally include no explicit representation of technologies. However, some (e.g., the SGM) (20) provide elaborate representation of technology costs. Owing to their aggregate representation, general equilibrium models are well suited for global analyses (**Table 1**) in which the world is generally divided into 10 or more regions. They can be also used for regional- and national-level analyses (**Table 1**), though the latter approach is more common.

Supplemental Material

3.3. Bottom-Up Models

Bottom-up models include highly disaggregated representation of the economy and a very detailed characterization of technologies. They also reflect an optimistic engineering paradigm (7). Many national-level country studies have been conducted using bottom-up modeling (**Table 2**; for reviews of related studies, see **Supplemental Appendix 2**) (also see 21–23). Bottom-up models are also used to assess the energy supply and demand aspects of technology-based policies that are not driven by price (e.g., labels and standards). Theoretically,

Table 1 Top-down models widely used for abatement analysis

Model	Institution	Theoretical framework
AIM CGE	National Institute for Environmental Studies, Japan	General equilibrium
MERGE	Electric Power Research Institute, United States	General equilibrium
GTEM	Australian Bureau of Agricultural and Resource Economics	General equilibrium
OECD-ENV-LINKAGES	Organisation for Economic Co-operation and Development, France	General equilibrium
SGM	Pacific Northwest National Laboratory (PNNL), United States	General equilibrium
PACE	ZEW GmbH Center for European Economic Research	General equilibrium
EPPA	Massachusetts Institute of Technology	General equilibrium
E3MG	Cambridge University	Macroeconomic
ERB	PNNL	Partial equilibrium
GEM-E3	National Technical University of Athens	General equilibrium
Phoenix	PNNL	General equilibrium

the "most efficient" technology within these models can lie beyond the production frontier determined by market behavior because customers may not actually adopt said technology. This discrepancy provides evidence of an efficiency gap (6). A high degree of detail regarding technology, such as its cost and efficiency, is included in bottom-up models, which allows

Table 2 Bottom-up models widely used for abatement analysis

Model	Institution	Theoretical framework
LEAP	Stockholm Environment Institute	Accounting framework
MARKAL	Energy Technology Systems Analysis Program (ETSAP)	Partial equilibrium
MESSAGE	International Institute for Applied Systems Analysis, Austria	Partial equilibrium
AIM-Enduse	AIM End (NIES), Japan	Partial equilibrium
TIMER	PBL, Netherlands Environmental Assessment Agency	Partial equilibrium
POLES	LEPII-EPE (Department of Energy and Environmental Policy), Université Pierre Mendès-France	Partial equilibrium
PRIMES	National Technical University of Athens	Partial equilibrium
AIM SNAPSHOT	NIES	Accounting framework
2050 Pathway tool	US Department of Energy and Climate Change	Accounting framework
LBNL China end-use energy model	Lawrence Berkeley National Laboratory (LBNL), United States	Accounting framework
TIMES	ETSAP	Partial equilibrium
TIAM-WORLD	ETSAP	Partial equilibrium
TIMES-VTT	ETSAP	Partial equilibrium
ISEEM	LBNL	Partial equilibrium

researchers to explore the potential of decoupling economic growth from energy demands.

Bottom-up models can be further divided into optimization and accounting models. Optimization models are based on a detailed representation of technologies involved in energy supply and demand. The information on technologies is recorded in terms of their capital, operating costs, and technical efficiencies. Models using optimization algorithms find the lowest costs for an energy system for a given discount rate. These models can analyze different energy markets (oil, gas, coal, etc.) and the interactions between them. Following a partial equilibrium approach with a focus on the energy sector, these models also assume that other sectors are not affected by changes in energy demand or the way this demand is serviced. However, this assumption has been moderated in some cases (e.g., elastic MARKAL endogenously links demand to energy prices).

Optimization models can be further differentiated on the basis of the solution approach (11, 24). Some optimization models assume perfect foresight behavior, which means agents have rational expectations about future events at the time of decision making. Other models (also known as dynamic recursive models) are solved assuming that market agents have myopic expectations and that investment and consumption decisions are made taking into consideration prices that prevail in a given time period.

In recent years, various bottom-up models have been developed on global and national scales to study energy strategies and planning. These models have different features and are often based on different methodological approaches. However, although these models are useful in predicting future trends, most consider the system as a whole and disregard the relationships between nations. Often, these models employ global or regional frameworks and depict energy systems and sectors of selected nations independently of each other (i.e., they ignore trading relationships and possible variations in production and energy consumption due to changes in trading volumes). Some bottom-up models, such as MARKAL, allow bilateral fuel trading between two regions. However, trading over commodities is disregarded. By contrast, ISEEM (industry-sector energy efficiency modeling) is specifically designed to evaluate and predict future commodities (e.g., steel, cement, etc.) and carbon trading as an alternative for reducing carbon emissions (25). ISEEM modeling brings a new perspective on carbon mitigation modeling by linking regional industry sectors via commodity trading relationships. Thus, the model aims to provide a suitable platform to analyze national-scale mitigation strategies such as energy efficiency measures as well as global-scale mitigation strategies such as commodity and carbon trading.

Unlike optimization models, accounting models do not include a detailed characterization of technologies. Instead, accounting models are generally used to carry out simulations of various policy options quickly. Therefore, they are useful for communicating results to policy makers and stakeholders. Their simulations are run to understand the implications of certain policy interventions on some indicators (e.g., CO_2 emissions). Therefore, these models are useful when using backcasting approaches. They also have high flexibility and can be modified to represent energy systems at any scale (cities, states, countries, regions).

3.4. Hybrid Models

Top-down models are short on technological details, whereas bottom-up models lack macroeconomic consistency. To address these deficiencies, two strategies have been followed. Soft linking is a practical strategy adapted to run a given scenario on both top-down and bottom-up models (**Figure 2**). It ensures macroeconomic consistency by making GDP growth comparable, e.g., certain GDP losses due to a carbon tax can be also be applied when calculating energy demands in the bottom-up models (27).

Researchers have also attempted to bridge the gap between top-down and bottom-up models either by incorporating macroeconomic

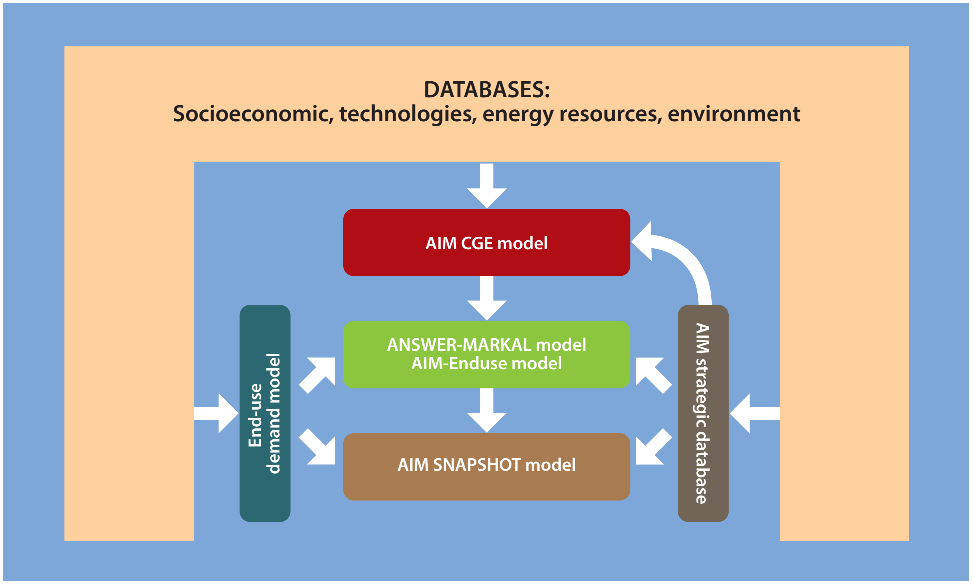


Figure 2

Framework for integrating the AIM CGE (Asia-Pacific Integrated Model computable general equilibrium) top-down model with the ANSWER-MARKAL bottom-up model (27).

feedback into bottom-up models or by including technological details in top-down models (28, 29). To that end, Bossetti and colleagues (30) developed the WITCH model, which allows improved representation of energy sectors in the Ramsey-Cass-Koopman optimal growth model. The MARKAL-MACRO model has also developed by linking the bottom-up, technologically rich MARKAL model with the intertemporal general equilibrium MACRO model. In the hybrid model, these approaches are solved simultaneously using a nonlinear optimization technique (5). The ReMIND model created by the Potsdam Institute for Climate Impact Research is another example of a hybrid model. The major challenges faced by these models are theoretical consistency, computational complexity, and policy relevance (13).

3.5. Integrated Assessment Models

Energy models have important limitations: Though they can estimate the lowest costs for mitigation using either energy system costs or social welfare, they suffer from two major shortcomings. First, they ignore the contribution of other human activities in sectors such as agriculture, forestry, and waste toward GHG emissions. Second, they do not help researchers generate an idea about the impacts of human activities on ecosystems and human beings. Around 1995, use of the IAM framework came into vogue (26) to address these concerns.

IAMs are typically composed of four modules (**Figure 3**) to understand the following issues: the impacts of human activities on GHG emissions, the implications of GHG emissions on atmospheric concentrations of GHG emissions, the implications of GHG concentrations on global temperatures and sea level, and the impacts of these changes on ecosystems. In summary, IAMs allow policy makers to understand the impacts of climate policies and, in some cases, to estimate the costs and benefits of climate actions (26). **Table 3** lists the IAM models that we analyze in Section 4.

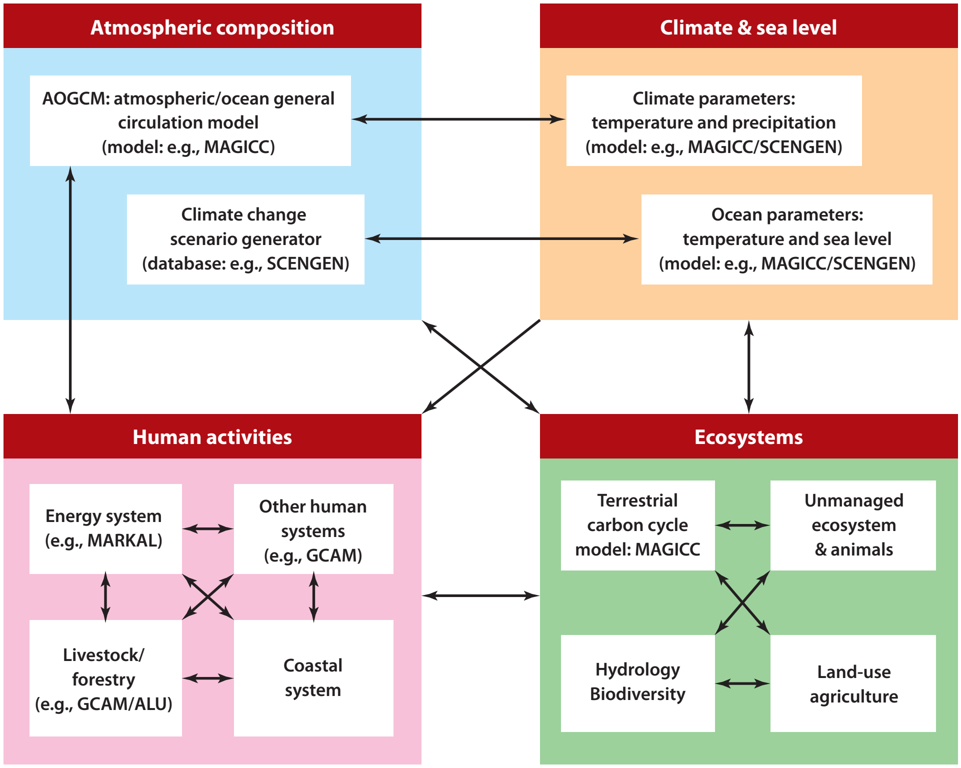


Figure 3

A typical integrated assessment model framework. Abbreviations: ALU, agriculture and land use; GCAM, global climate assessment model; MAGICC, model for assessment of greenhouse gas–induced climate change; SCENGEN, scenario generator.

3.6. Backcasting and Simulation Models

Traditional forecasting has been the dominant approach in futures-oriented studies. By contrast, backcasting is a relatively new approach. Robinson (31) first coined the term in 1982. Before him, Lovins (32) had proposed a "backward-looking analysis" as a long-term planning technique to investigate the supply and demand of electricity.

Table 3 Integrated assessment models widely used for carbon-mitigation analysis

Model	Institution
DICE	Yale University
DNE21	RITE (Research Institute of Innovative Technology for the Earth), Japan
GCAM	Pacific Northwest National Laboratory, USA
GRAPE	Institute of Applied Energy, Japan
IMAGE	RIVM, Netherlands National Institute for Public Health and the Environment
ENV-Linkages	Korea Economic Institute
MARIA-23	Tokyo University of Science, Japan

Table 4 Comparison between forecasting and backcasting

Stages	Forecasting	Backcasting
Vision	Evolutionary, organic, exploratory	Purposive, strategic
Perspective	Rule-based dynamics, observation, speculation and hedging, but no intervention with trends	Positive interventions to achieve societal goals, identification of desirable futures, strategic interventions
Process	Articulate alternate futures as scenarios; quantify key drivers of the future; project, but not predict, for each scenario the trends of indicators	Articulate goals and targets to be achieved in alternate futures, find roadmaps of actions to realize the goals and targets in each future, discover constraints to achieve goals and targets
Methods	Econometric models for short-term forecasting, dynamic general equilibrium algorithms for long-term projections	Dynamic models taking backward steps from future goals and targets to the present to identify roadmap of actions to achieve goal and targets while overcoming external constraints and limitations
Techniques and tools	Mathematical programming; forward pass algorithms; simulation, econometrics; computable general equilibrium models	Backward pass algorithms, dynamic programing

According to Robinson, the purpose of backcasting is not to produce blueprints, but to indicate the relative feasibility as well as the social, environmental, and political implications of different energy futures on the assumption of a clear relationship between goal setting and policy planning (**Table 4**). The objectives of backcasting (e.g., the IAM-NIES model) are to explore and identify near-term actions required to attain long-term future goals. Backcasting is typically used to analyze long-term complex issues involving many aspects of society as well as technological innovations and change (33).

4. GLOBAL AND REGIONAL ESTIMATES OF ENERGY AND EMISSIONS ACROSS SCENARIOS

Global and regional scenarios of energy consumption and CO_2 emissions play key roles in global policy makers' understanding of the magnitude of emission abatement required, the short- and long-term costs involved, and the regional implications of emission mitigation policies. Because many alternative modeling approaches are available, intermodal comparison exercises are useful for getting insights from scenarios run using a suite of economy-energy-environment models. Below, some modeling applications discussed in Section 3 are discussed in further detail. In particular, the Asian modeling exercise provides an important contribution: Twenty-three modeling teams were involved in analyzing important issues for modeling energy and emission scenarios for major regions of Asia. Most of the models used are global, so data were also collected for other regions that will play important roles in global emission mitigation policies.

4.1. Drivers of Energy Demand and Emissions

The range of future populations assumed across various models is much lower than the range of GDPs, which is an important driver of energy demand. Although population is an exogenous variable for all models, GDP is assumed to be either exogenous or endogenous, depending on the model used. For computable general equilibrium (CGE) models such as AIM (Asia-Pacific model) CGE and iPETS, GDP is determined endogenously; for partial equilibrium models such as GCAM and MESSAGE, it is an exogenous assumption. **Figure 4** shows the global GDP and population as well as primary energy consumption and fossil-fuel emissions. Global population increases from

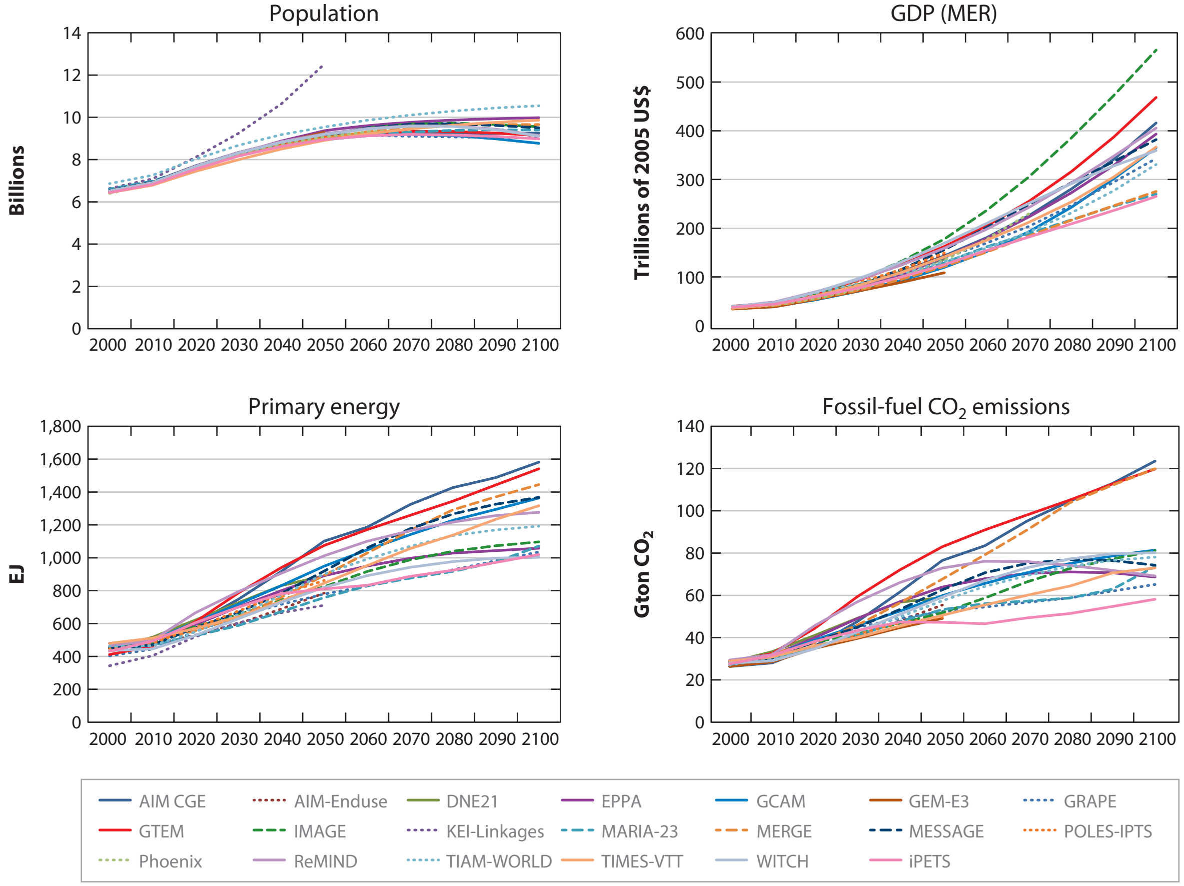


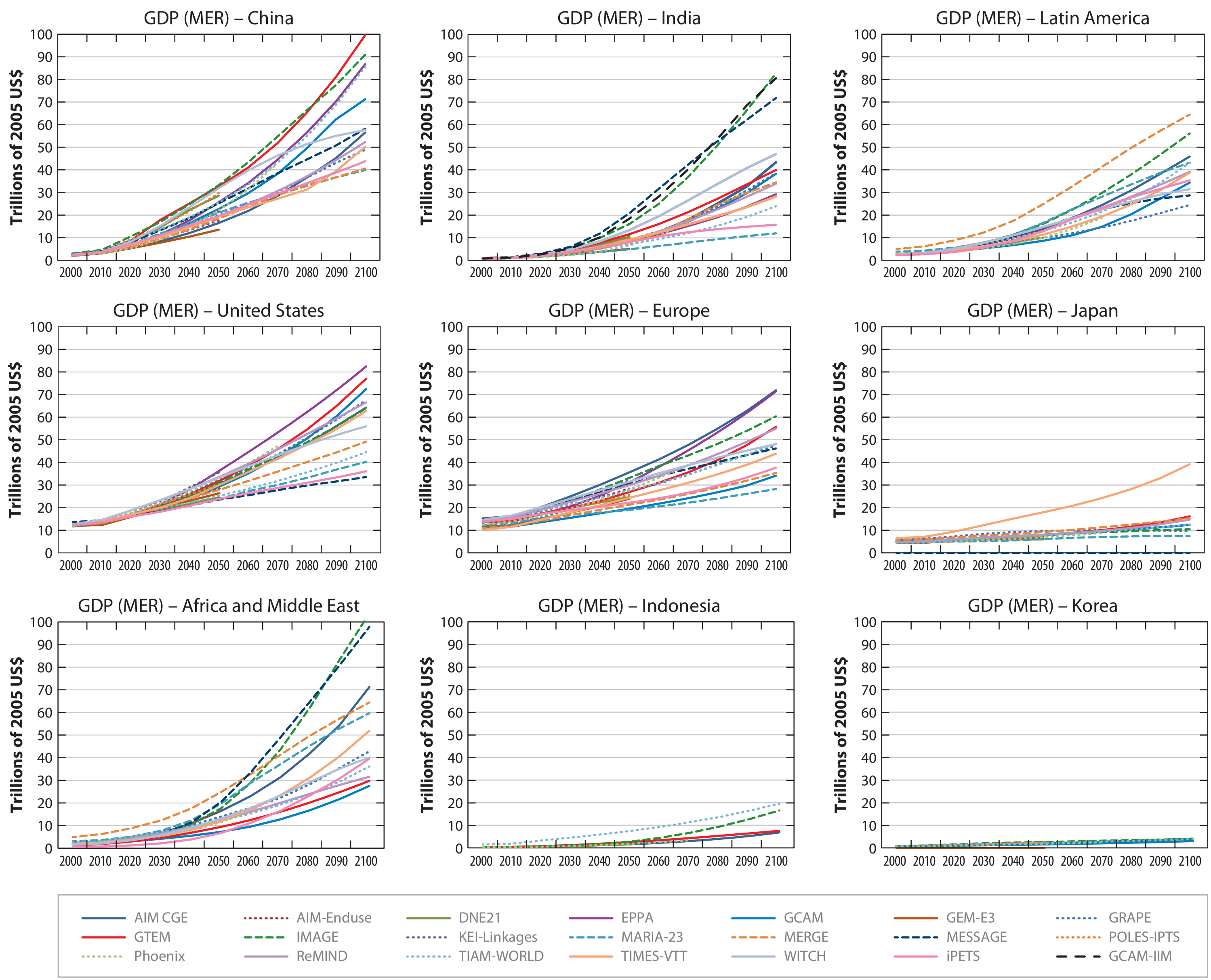
Figure 4

Global population, GDP, primary energy, and CO_2 emissions across models in the reference scenario. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**). Abbreviations: GDP, gross domestic product; MER, market exchange rate.

6.5 billion in 2005 to a median of 9.3 billion in 2095. At the same time, global GDP increases ninefold from more than $41 trillion (in 2005 prices) in 2005 to a median value of $376 trillion in 2095. This increase implies that the average global per capita income also increases more than sevenfold.

China, India, Latin America, and the Middle East and Africa (MAF) regions are the primary drivers of global GDP growth. The highest GDP in 2100 (average across models) is observed in China at $63 trillion, followed by the United States ($58 trillion), the MAF ($53 trillion), Europe ($49 trillion), Latin America ($40 trillion), and India ($38 trillion) (**Figure 5**). Compared with other regions, the variation is high across models for the MAF (ranging from $30 to $100 trillion) and India (ranging from $12 to $80 trillion). Comparison of the 2011 GDP values is based on the respective 2005 GDP values for each of the regions: China at $2.2 trillion, the United States at $12.5 trillion, the MAF at $2 trillion, Europe at $13 trillion, Latin America at $2.7 trillion, and India at $0.8 trillion.

Population growth is mainly concentrated in the MAF, followed by India and Latin America. For all other regions, it is fairly stable. Population assumptions for the MAF show wide variation, as the regional definitions


GDP (MER) – China
GDP (MER) – India
GDP (MER) – Latin America
GDP (MER) – United States
GDP (MER) – Europe
GDP (MER) – Japan
GDP (MER) – Africa and Middle East
GDP (MER) – Indonesia
GDP (MER) – Korea
Trillions of 2005 US$
AIM CGE
AIM-Enduse
DNE21
EPPA
GCAM
GEM-E3
GRAPE
GTEM
IMAGE
KEI-Linkages
MARIA-23
MERGE
MESSAGE
POLES-IPTS
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differ across models (**Figure 6**). However, most models (except for four) converge to a population of 9 billion in 2100 for this region. For India and China, population hovers around 1.5 billion for a large part of this century: For India, population shows the greatest increase after 2050; for China, population declines after 2050.

4.2. Reference Scenario: Primary Energy Consumption, Emissions, and Energy Technologies

Following the dominance of China in global GDP, primary energy consumption in China across models is also higher relative to other regions, though the maximum increase across the century happens in India (**Figure 7**). Primary energy consumption in 2005 is approximately 92 exajoules (EJ) for the United States, 72 EJ for Europe, 60 EJ for China, 44 EJ for the MAF, 26 EJ for Latin America, and 21 EJ for India. These values increase in 2095 to an average of 132 EJ, 99 EJ, 276 EJ, 222 EJ, 96 EJ, and 151 EJ, respectively. The relative increase in primary energy consumption during this period is highest for India at 7.3 times, followed by that in Africa at 5 times. In many developing regions, such as China and India, there is substantial consumption of traditional biomass in 2005. By contrast, in the developed regions such as the United States and Europe, almost all energy consumption is commercially traded energy. The primary energy consumption scenarios in 2095, however, consist of negligible traditional biomass for currently developing regions because of their rapid economic growth and access to modern fuels.

The reference scenario shows trajectories of CO_2 emissions very similar to those of primary energy consumption, as most of the primary energy consumption across regions throughout the century is based on carbon-intensive fossil fuels (**Figure 8**). CO_2 emissions from China will dominate global emissions with almost 22-Gton CO_2 emissions (average across models) in 2095, followed by the MAF with 14.5-Gton CO_2, India with 10.4-Gton CO_2, the United States with 8.5-Gton CO_2, Europe with 6-Gton CO_2, and Latin America with less than 5-Gton CO_2. As with primary energy consumption, the highest increase between 2005 and 2095 occurs in India, whose 8.3-fold increase is followed by a more than 6-fold increase in the MAF.

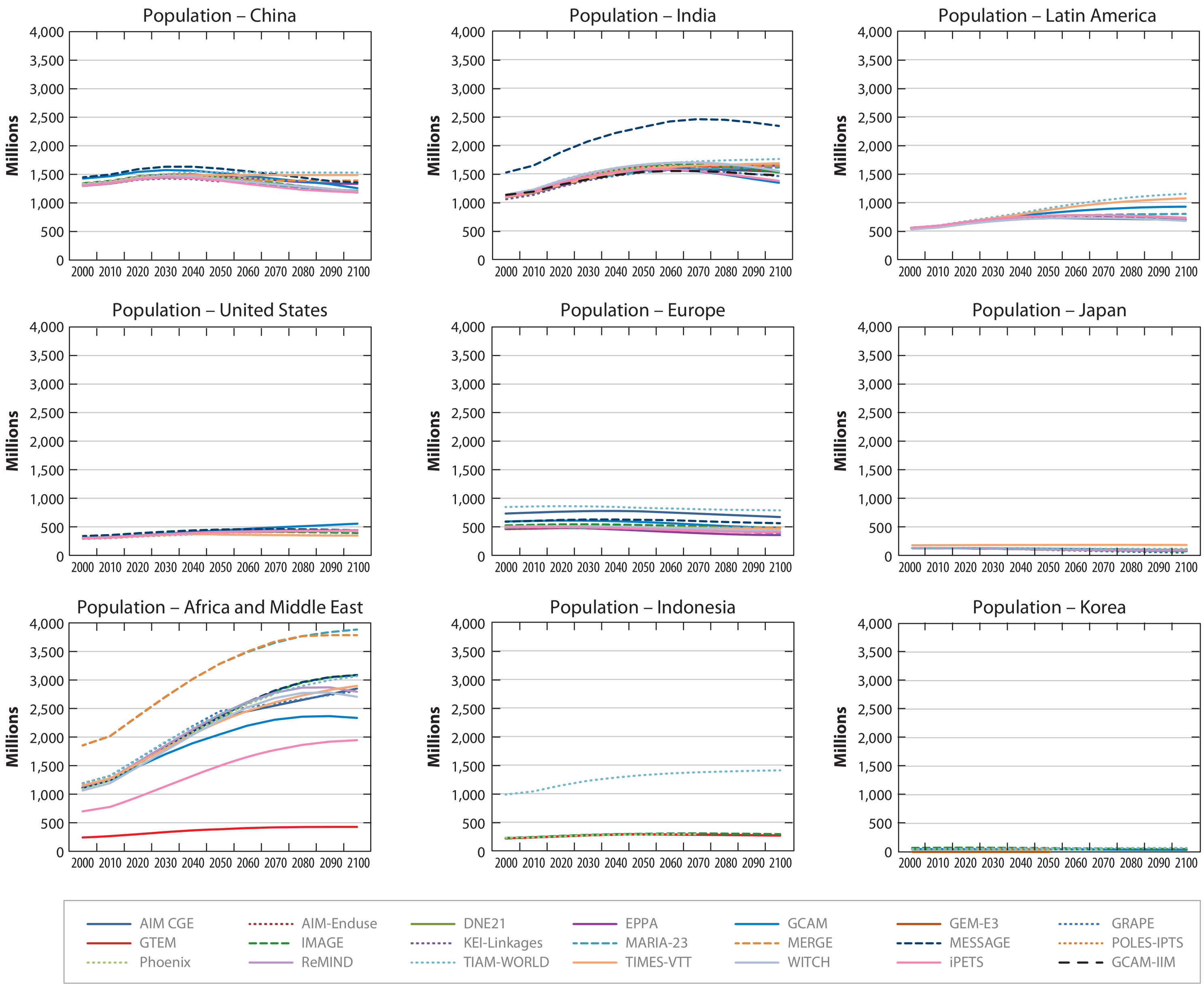
In terms of technology share in the electricity sector, fossil fuels dominate electricity production across most models; on average, their share is 60% in 2100. However, there is significant variation across models. MESSAGE, TIAM, and ReMIND show a much lower share of fossil fuels. The average global share of nuclear energy is 14% across models. The average global share of wind energy across models is 8% in 2095. The share of solar energy in the reference scenario is less than 3% for all the models except for MESSAGE and ReMIND. For those two models, the global share of solar energy in 2100 is 49% and 36%, respectively. According to ReMIND, Africa, China, Latin America, and the United States hold a 40% share of total electricity generation in 2095. By contrast, per MESSAGE, the share of solar energy in 2100 is 80% in the MAF and 40% in southern Asia (including India). Wind energy has an average share of 12–15% in Latin America, the United States, and Europe in 2100. By the end of the century, nuclear energy takes a high average share in Japan and South Korea at approximately 25% and 30%, respectively, followed by India at 20% and China at 17%.

4.3. Climate Policy Scenario: Primary Energy Consumption, Emissions, and Energy Technologies

The low-carbon scenario leads to an atmospheric CO_2 concentration ranging from

Figure 5

GDP across model regions. Abbreviations: GDP, gross domestic product; MER, market exchange rate. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).


Population – China
Population – India
Population – Latin America
Population – United States
Population – Europe
Population – Japan
Population – Africa and Middle East
Population – Indonesia
Population – Korea
Millions
0
500
1,000
1,500
2,000
2,500
3,000
3,500
4,000
2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100
AIM CGE
AIM-Enduse
DNE21
EPPA
GCAM
GEM-E3
GRAPE
GTEM
IMAGE
KEI-Linkages
MARIA-23
MERGE
MESSAGE
POLES-IPTS
Phoenix
ReMIND
TIAM-WORLD
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GCAM-IIM

350-ppmv CO_2 to 430-ppmv CO_2 across models in 2100. Compared with the reference scenario, this scenario leads to an average reduction in global primary energy consumption of 30% by 2100. However, rapid decarbonization of energy leads to a significant drop in CO_2 emissions across the century (**Figure 9**). Emission stabilization and declines are observed after 2020 in most models. Global emissions return to 2005 levels across most models by 2035. Many models (GCAM, MESSAGE, ReMIND, TIAM, and WITCH) also report significant negative emissions mainly in the latter part of the century, although other models report a significant decline. Apart from EPPA and MERGE, which show emissions in 2095 to be greater than 12-Gton CO_2 and to reach 4.7-Gton CO_2, respectively, all models report emissions below 3-Gton CO_2. GCAM shows the highest negative emissions with 14.5-Gton CO_2 sequestered from the atmosphere in 2095.

The highest reduction in average primary energy consumption across models in 2095 relative to the reference scenario is observed in South Korea at 46%, followed by Europe at 40% (**Figure 10**). In the three big economies of China, India, and the United States, the reduction in primary energy consumption is 33–34%, followed by 29% in Indonesia. Latin America has the lowest reduction in primary energy consumption at only 9% in 2095, whereas this reduction is approximately 20% in all other regions. Even under the climate policy scenario, China, India, and the MAF dominate in primary energy consumption.

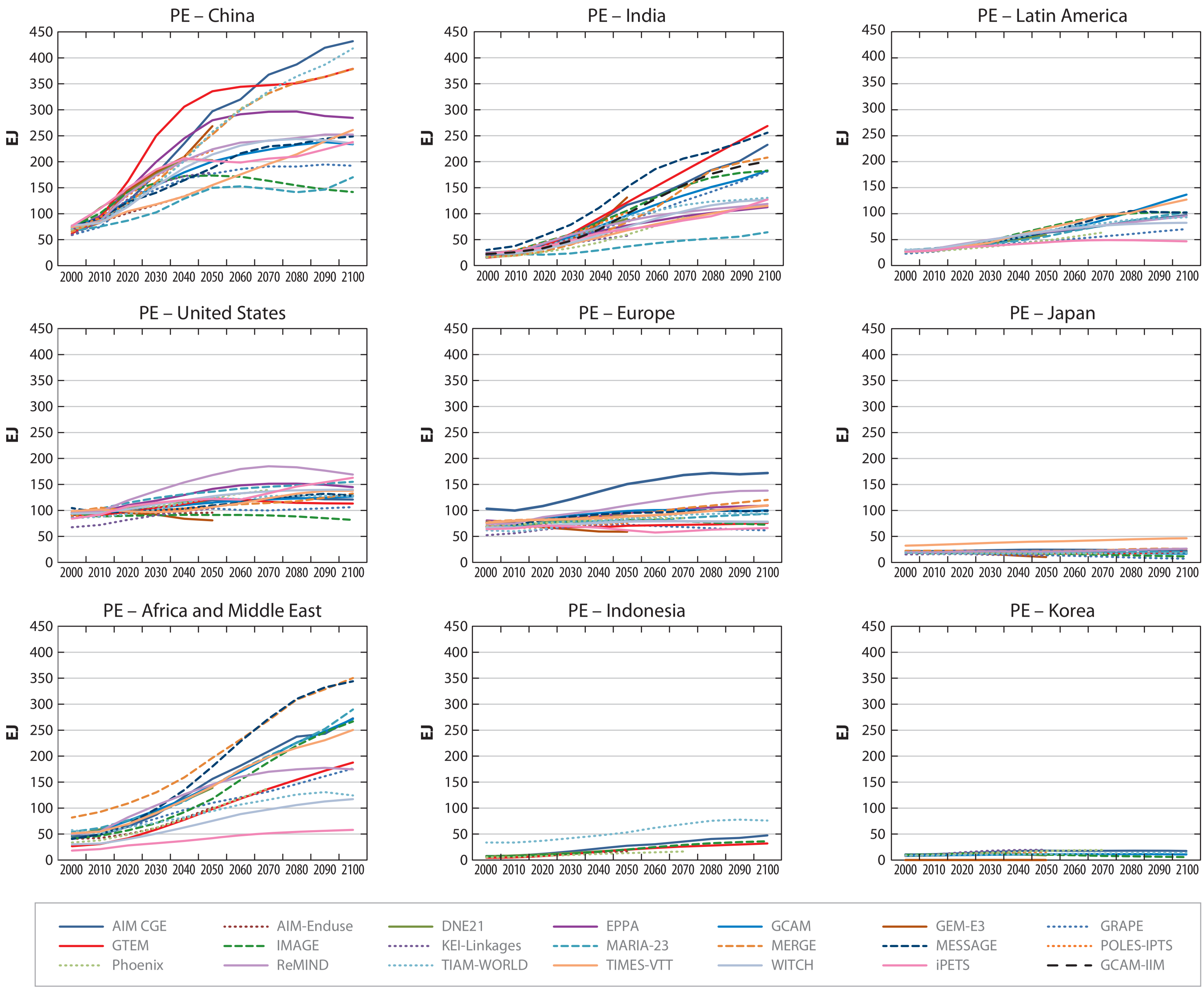
China, Africa, and India undertake the bulk of emission reductions, mainly because these regions witness the highest emissions under the reference scenario. Compared with the reference scenario, emission reduction in 2100 is 21-Gton CO_2 for China, 15-Gton CO_2 for Africa, and 10-Gton CO_2 for India (**Figure 11**). CCS technology plays an important role in emission mitigation in these regions, particularly in the first half of the century. The share of this technology plus fossil fuels in total electricity production in 2050 is 41% for the MAF, 30% for China, and 17% for India. The United States and Europe are also important regions: Their respective shares of CCS are 25% and 18% in 2050. Post-2050, however, the share of this technology declines in favor of other technologies. Though fossil-fuel technologies continue declining post-2050, biomass with CCS in electricity production increases across all regions except India: Its share in 2100 ranges from 5% to 10% for all regions except South Korea, Indonesia, and Latin America. Although smaller in the former two regions, in Latin America the share of this technology is 21% in 2100. Accordingly, Latin America is a big player in terms of bioenergy production.

Nuclear energy is critical for India: Models project it will occupy an average share of 58% of total electricity generation in 2100. For South Korea, nuclear technology is critical in both the short and long term (**Figure 12**). By 2100, the projected share of nuclear technology will be 45% for China and Japan and 35% for the United States and Europe. Wind technology also plays a critical role in emissions mitigation in Latin America, Europe, the United States, and the MAF. The average share of electricity generation in 2100 is close to 25% for Latin America and 20% for all the latter regions. Solar energy plays a very important role in emissions mitigation in Africa, China, and India: By 2100, models predict its share of electricity generation will be 48%, 38%, and 36%, respectively.

An output of these models for energy systems in China and India is the important role played by nuclear and CCS technologies. Four reasons are provided to account for this finding. First, because China and India are rapidly growing countries, their demands for

Figure 6

Population across model regions. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).


PE – China
PE – India
PE – Latin America
PE – United States
PE – Europe
PE – Japan
PE – Africa and Middle East
PE – Indonesia
PE – Korea
EJ
AIM CGE
AIM-Enduse
DNE21
EPPA
GCAM
GEM-E3
GRAPE
GTEM
IMAGE
KEI-Linkages
MARIA-23
MERGE
MESSAGE
POLES-IPTS
Phoenix
ReMIND
TIAM-WORLD
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energy production are rising rapidly. Second, in a carbon-constrained world, this rapid demand has to be met by low-carbon sources. Although most models include a constraint on the share or growth rate of nuclear and CCS technologies, they provide no resource constraints for these technologies. By contrast, renewable technologies have a constraint on their resource base, which guides their maximum allowable penetration.

Third, the cost of renewable energy technologies is currently high relative to that of nuclear technology. At present, though CCS is much more expensive, models assume a rapid decline in its cost. CSS can also be used with existing fossil technologies, which gives it an edge. Fourth, models do not include many constraints related to the proliferation, waste disposal, and safety aspects of nuclear energy. Including these costs implies valuing these aspects in monetary terms, which is debatable. In addition, no constraints or limits on CCS are assumed for most regions.

As an alternative to achieve the global carbon mitigation goal, Karali and colleagues (33) considered commodity trading. They used the ISEEM modeling framework to develop an energy model for the iron and steel sector of three countries (the United States, China, and India). Their ISEEM-IS model is used to estimate and evaluate carbon emissions through alternative mitigation options, such as policies (e.g., carbon caps), commodity trading, and carbon trading. It is also used to gain a better understanding of carbon-mitigation potentials while including technological and economic implications. The model engages the following scenarios, which are briefly defined and then analyzed below:

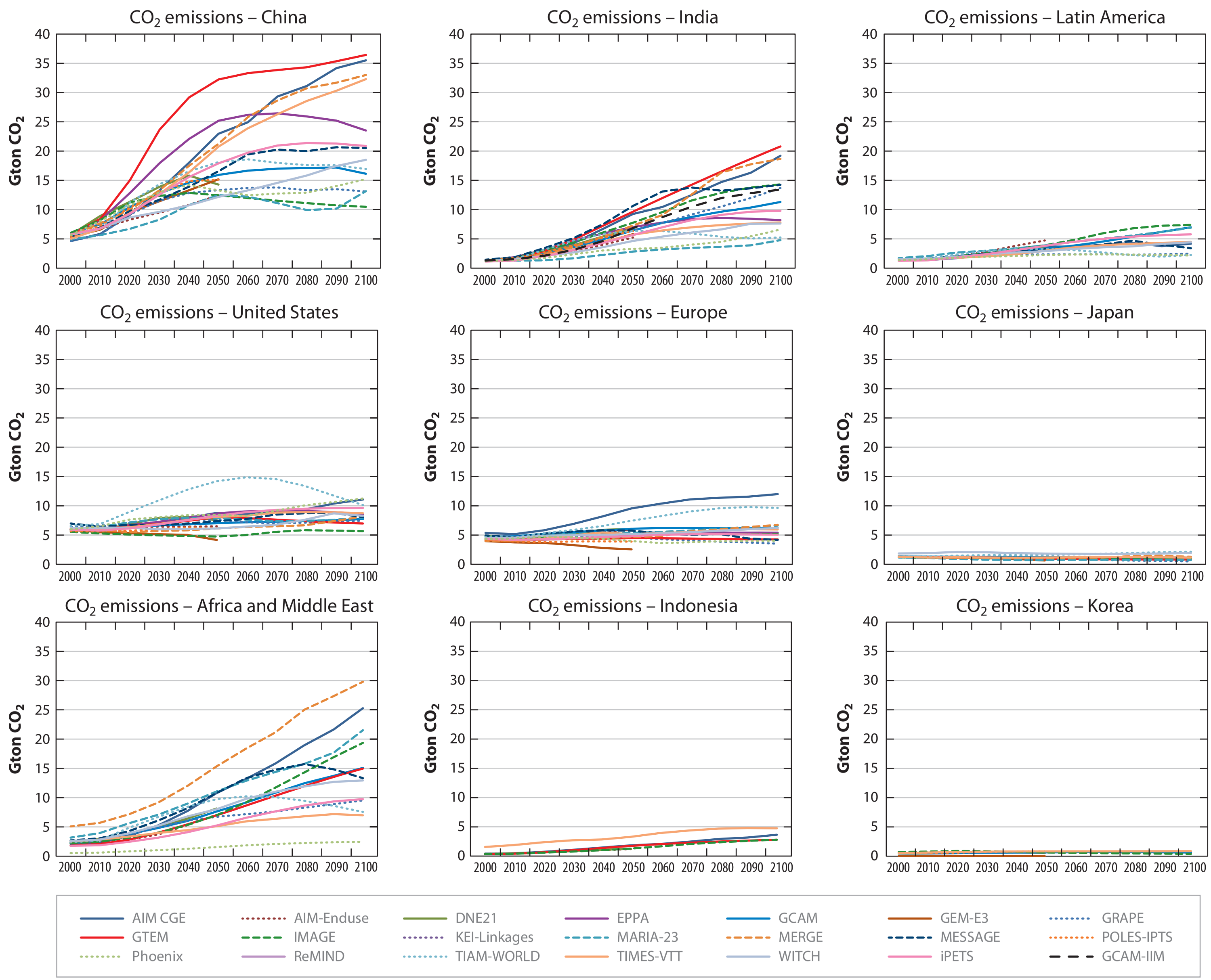
- Base scenario: the development of the iron and steel sector under current trends
- Base-E scenario: the same assumptions and trends as in the Base scenario plus efficient production technologies (i.e., energy efficiency improvements of current production technologies with extra costs)
- Emission reduction without trading (ER) scenario: 10% emission restriction below those in the Base scenario for each country
- Emission reduction with commodity (steel) trading (ET) scenario: 10% emission reduction (i.e., carbon cap) in the US iron and steel sector through the planning horizon with commodity trading opportunities from India and China but with no carbon cap on Chinese and Indian iron and steel production
- Emission reduction with carbon trading (EC) scenario: 10% global emission reduction through the planning horizon with carbon trading opportunities for the United States from India and China

Compared with the Base and Base-E scenarios, steel production in the United States decreases in the ET and EC scenarios. The rest of the US steel demand is satisfied by imports from China and India. Accordingly, steel production in China and India increases in the ET and EC scenarios. China accounts for 75% of total US steel imports because of its lower production costs. In the Base and Base-E scenarios, China has the cheapest production costs, compared with those in the United States and India, through the planning horizon. Thus, the ISEEM-IS optimization process tends to realize all imports of the United States from China until the upper-bound assumptions are reached (i.e., shares of China in the total US imports from China and India are limited to 75% in the ET and EC scenarios).

Figure 13 displays the energy consumptions of the iron and steel sector in the United States, China, and India under different mitigation scenarios applied in the ISEEM-IS model. All scenarios decrease carbon emissions compared

Figure 7

Primary energy (PE) consumption across model regions. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).


CO2 emissions – China
CO2 emissions – India
CO2 emissions – Latin America
CO2 emissions – United States
CO2 emissions – Europe
CO2 emissions – Japan
CO2 emissions – Africa and Middle East
CO2 emissions – Indonesia
CO2 emissions – Korea
Gton CO2
0 5 10 15 20 25 30 35 40
2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100
AIM CGE
AIM-Enduse
DNE21
EPPA
GCAM
GEM-E3
GRAPE
GTEM
IMAGE
KEI-Linkages
MARIA-23
MERGE
MESSAGE
POLES-IPTS
Phoenix
ReMIND
TIAM-WORLD
TIMES-VTT
WITCH
iPETS
GCAM-IIM

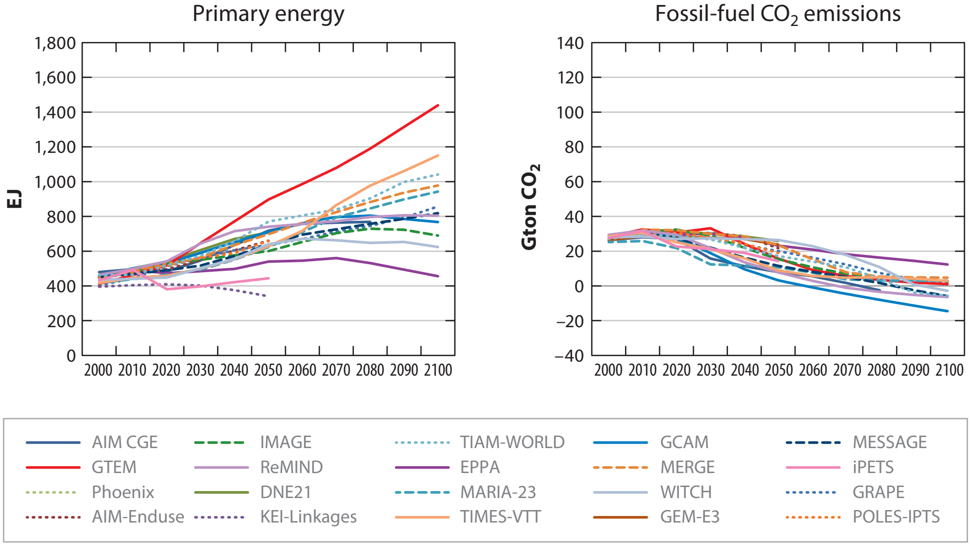


Figure 9

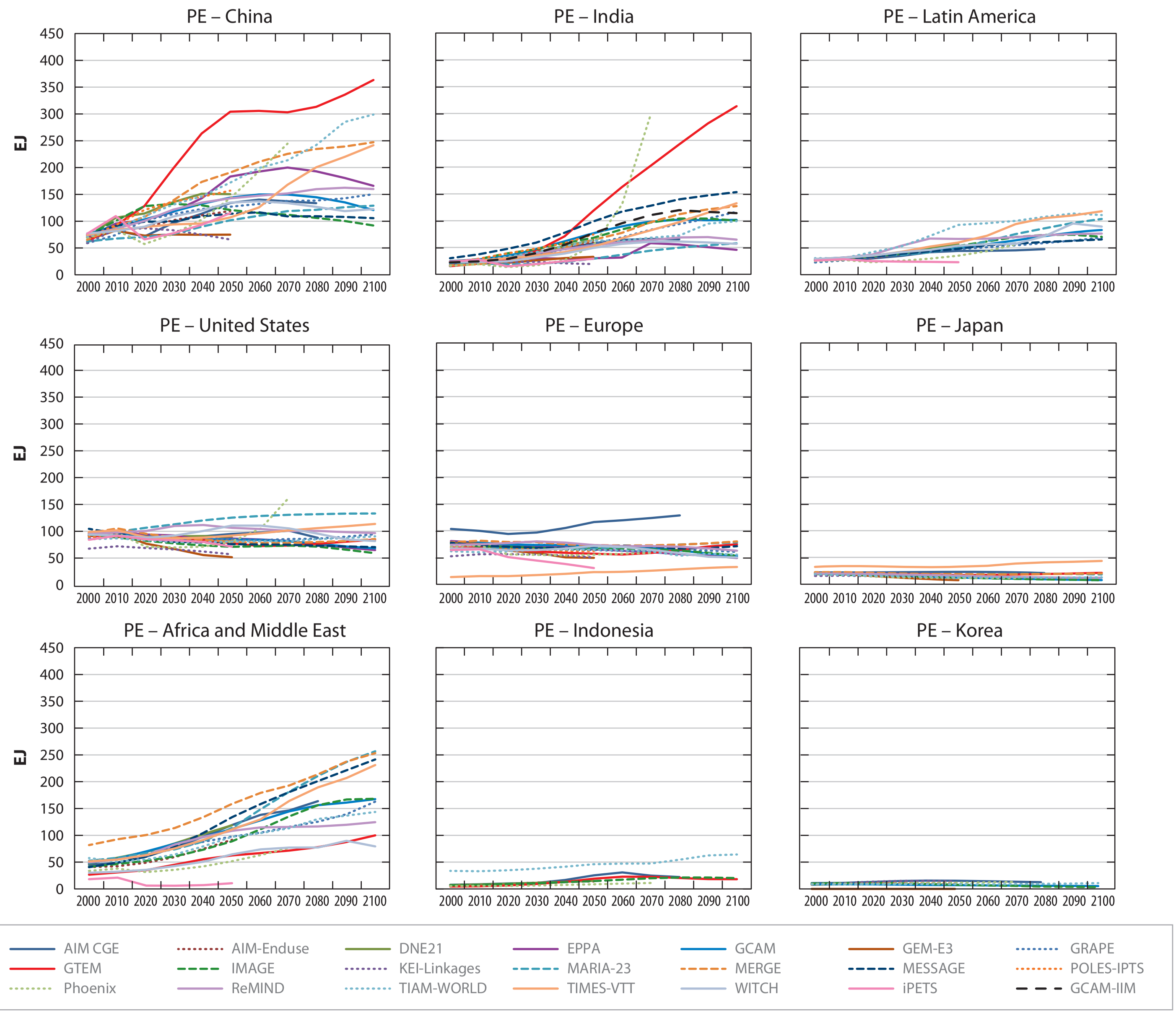
Global primary energy consumption and CO_2 emissions under the climate policy scenario. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).

with the Base scenario in the US iron and steel sector. The reduction in the Base-E scenario is due to the investments on cost-effective efficiency measures input into the ISEEM-IS model. However, the reduction levels are higher under the ER, ET, and EC scenarios with a 10% carbon cap. The ET and EC scenarios provide identical, but the lowest, reduction levels for the US iron and steel sector. Thus, commodity and carbon trading are better alternatives for the US iron and steel sector in terms of carbon mitigation, compared with the national-scale efficiency measures. By contrast, the iron and steel sector in China has lower energy consumptions in the ER and EC scenarios, in which a 10% carbon cap is applicable. In India, the iron and steel sector dominates the cost-effective efficiency measures. As shown in **Table 5**, the Base-E scenario satisfies the 10% emission reduction requirements of the ER and EC scenarios in India until 2030. Thus, the emission intensity results in the ER and EC scenarios for India are similar to those in the Base-E scenarios. After 2040, however, some efficiency investments are observed in the iron and steel sector in India in the ER and EC scenarios, compared with the Base-E and ET scenarios.

However, there are no improvements in the iron and steel sector for China and India under the ET scenario, in which steel production is increased owing to increasing exports to the United States, but no carbon cap is applied. Thus, decreasing emissions in the US iron and steel sector alone via the commodity trading strategy (i.e., increasing steel imports) in the ET scenario does not result in a reduction of net global emissions or global risks in climate change. Instead, this scenario results in a simple transfer of actual production burdens to China

Figure 8

CO_2 emissions across model regions. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).


PE – China
PE – India
PE – Latin America
PE – United States
PE – Europe
PE – Japan
PE – Africa and Middle East
PE – Indonesia
PE – Korea
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2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100
AIM CGE
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and India where actual intensities of energy use and emissions are higher.

Instead, energy intensity trends in **Figure 14** indicate a different perspective. Even though energy consumptions decline in the US iron and steel sector, there is almost no improvement to energy intensities, except within the ER scenario, in which national-scale efficiency measures are applied to mitigate carbon emissions. In the ET and EC scenarios where steel trading is available, there is no efficiency improvement on the US iron and steel sector. Thus, importing from China and India (either with commodity or carbon trading) is cheaper for the United States compared with making investments in national efficiency improvements. In the iron and steel sector in China, efficiency is improved in the ER and EC scenarios in which a 10% carbon cap is applicable. By contrast, in the iron and steel sector in India, all scenarios provide similar energy-intensity levels, which are very close to those in the Base-E scenario but much lower than in the Base scenario.

As shown in **Figure 15**, owing to the dominance of cost-effective efficiency measures in the iron and steel sector in India, carbon mitigation costs are negative in all scenarios where a carbon cap is applied. In the United States, because carbon mitigation is primarily a result of steel trading in the ET and EC scenarios, there is no associated mitigation cost. In the ER scenario, by contrast, carbon mitigation costs due to efficiency investments become cost-effective after 2035. In the iron and steel sector in China, the cost-effectiveness of carbon mitigation is realized after 2045 in both the ER and EC scenarios.

5. LIMITATIONS OF APPROACHES AND ESTIMATES

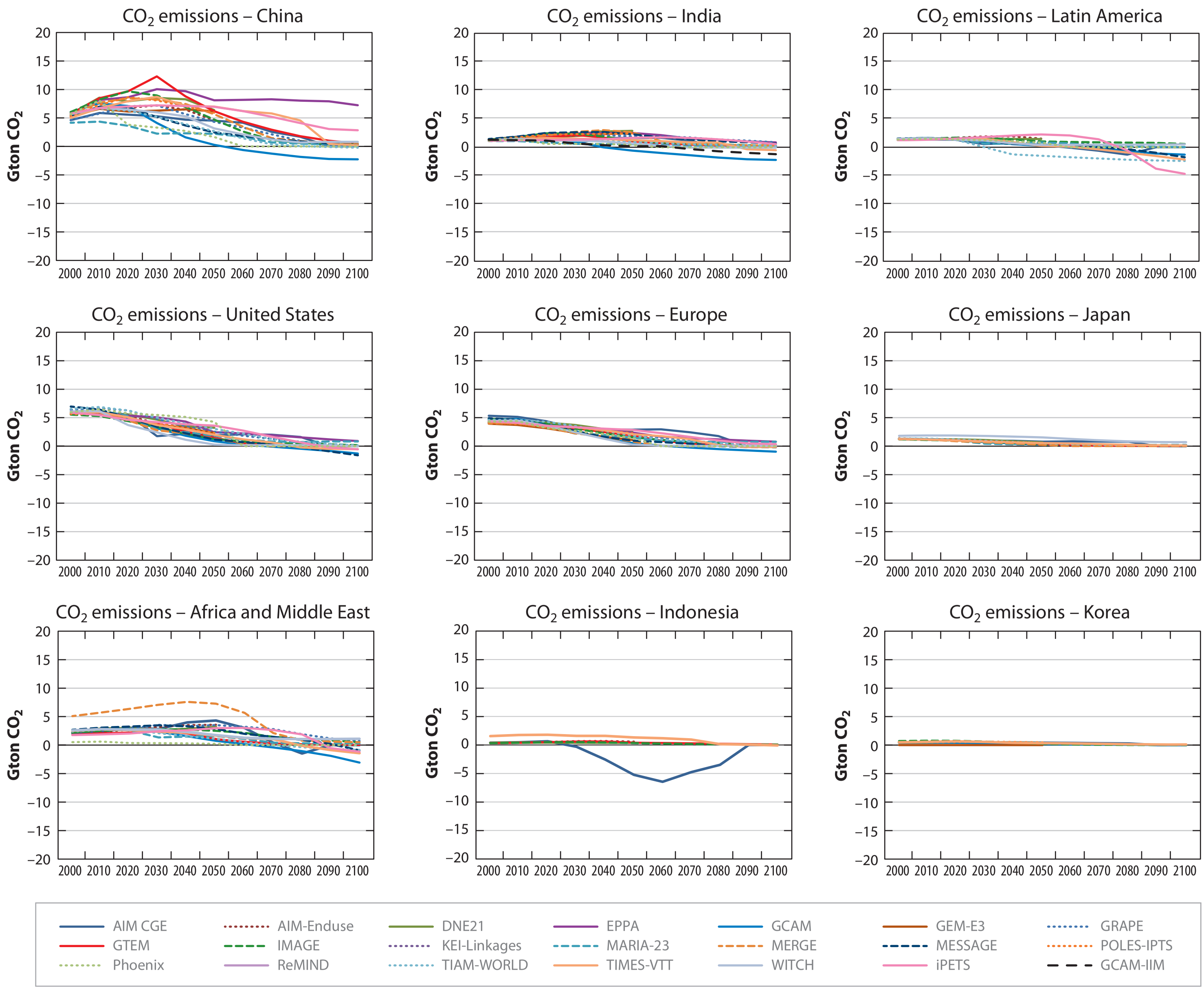
The purpose of energy modeling is principally determined by the intention to forecast and anticipate future energy supply performances or to simulate energy consumption reactions for scenario analysis. The modeling frameworks should be seen as tools for generating insights on how the future may develop under a given set of assumptions of important driving factors such as climate policies, resources, technology progress, etc. However, one must interpret the results provided by the models with care and be aware of both the limitations of such models and their results regarding the input structure. From this point of view, the aim of this section is to provide a summary of the limitations on the modeling approaches described in Section 3.

In recent years, various kinds of global and national energy, environment, and climate models have been proposed. These models have different features and are often based on different methodological approaches. However, even though most models are useful in predicting future trends, in practice, challenges such as vast data needs, inflexible structures, new and emerging technology descriptions, and behavioral impacts on technology selections make them difficult to deploy (25). In addition, most energy modeling approaches have rational expectations. They consider all future events such as price dynamics, energy source availabilities, and technology changes with perfect knowledge. However, it is questionable that the market would anticipate the future with perfect knowledge for the next 50 or 100 years, as is assumed in a rational expectations model. In general, important features that are largely missing from existing modeling frameworks are as follows:

- Uncertainty about technological change: Technology descriptions are typically modeled as exogenous inputs to the models. Once described, the technological specifications are considered not to change throughout the years.

Figure 10

Primary energy (PE) consumption across model regions under the climate policy scenario. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).


CO2 emissions – China
CO2 emissions – India
CO2 emissions – Latin America
CO2 emissions – United States
CO2 emissions – Europe
CO2 emissions – Japan
CO2 emissions – Africa and Middle East
CO2 emissions – Indonesia
CO2 emissions – Korea
Gton CO2
20 15 10 5 0 –5 –10 –15 –20
2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100
AIM CGE
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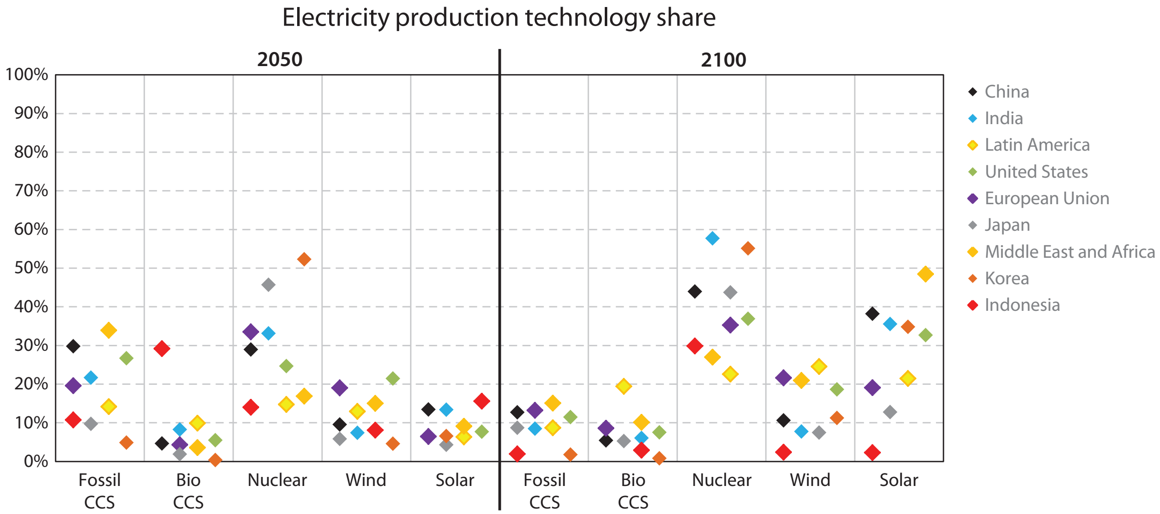

Figure 12

Share (%) of electricity production technology under the climate policy scenario for major regions. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**). Abbreviations: Bio CCS, biomass with carbon capture and storage; Fossil CCS, fossil fuels with carbon capture and storage.

- Vast data requirements: Data availability underlies many challenges. Some data needed for inputting into the models are either unavailable or difficult to procure.
- Increasing model complexity: The interactions among the energy system, society, and the climate system are very complex, and they involve linkages that are not well known.
- Flexibility: Most models and data sets remain closed source owing to the protection of intellectual property. This situation reduces the flexibility and applicability of models to different climate policies.

As discussed in Section 3, there are two widespread modeling approaches for the assessment of economic impacts triggered by energy policies: bottom-up and top-down models. These approaches differ mainly with respect to the emphasis they place on the technological details of the energy system and their representation of economic relationships. They both have advantages and disadvantages and are criticized in several respects.

Top-down models, for example, do not capture the detail necessary for the energy sector and under-represent the complex interactions among demand and supply options (8, 35). These models can help policy makers to assess the macroeconomic impacts (such as overall changes in GDP, consumption, investments, imports, and foreign exchange) of particular market instruments such as a carbon tax on energy systems or subsidies on renewable energy generation (25). However, energy-economy interactions provide a limited representation of the underlying energy system. The energy sector, as with all sectors, is mostly represented in an aggregate way, but these models cannot integrate technological innovations with the necessary level of detail. As a result, advanced

Figure 11

CO_2 emissions projected by model for various regions under climate policy scenarios. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**).

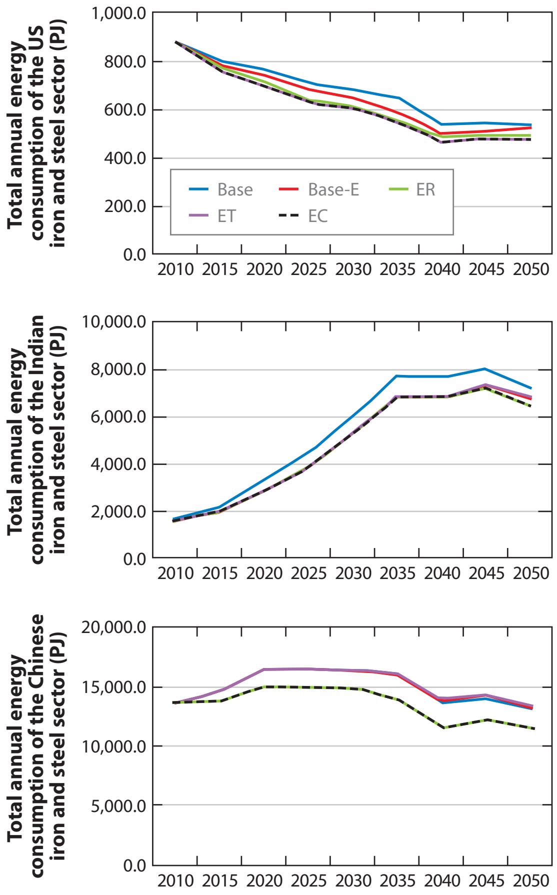

Figure 13

Total annual energy consumption in petajoules (PJ) of the iron and steel sector for the United States, India, and China based on predictions from the Base, Base-E, ER, ET, and EC scenarios. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**). Abbreviations: Base, development of the iron and steel sector under current trends; Base-E, the Base scenario plus efficient technologies; EC, emission reduction with carbon trading; ER, emission reduction without trading; ET, emission reduction with commodity trading.

future technologies and fuel options are not well represented.

Bottom-up models, in contrast, are built with deep technological detail including technical performances and cost structures of future technologies (36). They include a great number of discrete energy technologies to capture the substitution of energy sources on primary and final energy levels. They also include process substitutions and efficiency improvements (25). Each energy-consuming technology is identified by a detailed description of input-output structures, cost dynamics, and other technical and economic characteristics. However, such models often neglect the macroeconomic impacts of energy policies.

The variations across model structures and key assumptions yield different results. Some of these variations and their impacts are briefly discussed below:

1. Assumptions about energy demand drivers (i.e., GDP and population) differ across models. For example, the range of near- and long-term GDP growth assumed by different models for India shows great variation. However, many frameworks model drivers endogenously: For example, general equilibrium models project GDP endogenously, whereas other frameworks (bottom-up models) require those drivers as exogenous inputs.
2. Differences in assumptions about resource costs and performance parameters reflect the modeling teams' assumptions about the relative costs associated with energy production from different technologies.
3. How models represent the growth of technologies is also important. For CCS, nuclear, wind, solar, and hydroelectric technologies as well as, though to a lesser degree, fossil technology for electricity generation, the variation among models is great: They can assume no constraint, a growth-rate constraint, a constraint on the share of technologies, or no technology at all.
4. The process of calibrating base year shares as well as how this calibration affects the future evolution of technologies are important. Many models, such as GCAM and general equilibrium models, calibrate energy systems to the base year share of technologies, whereas others models, such as MESSAGE and AIM-Enduse, do not calibrate base year shares. Thus, in the former models, the base year shares affect the evolution of future

Table 5 Total annual CO_2 (Mton) emissions from the United States, China, and India predicted for multiple scenarios across three decades

Scenario[a]	United States			China			India		
	2010	2030	2050	2010	2030	2050	2010	2030	2050
Base	99.7	64.0	49.7	1479.1	1760.1	1381.8	160.8	545.1	621.9
Base-E	99.7	62.4	48.4	1479.1	1757.4	1399.4	157.6	482.0	596.5
ER	99.7	57.6	44.6	1479.1	1580.0	1168.0	157.6	482.3	560.0
ET	99.7	57.6	44.6	1479.1	1765.4	1408.7	157.7	483.0	597.3
EC	99.7	57.6	44.6	1479.1	1580.0	1175.0	157.7	483.3	560.0

[a]Abbreviations: Base, development of the iron and steel sector under current trends; Base-E, the Base scenario plus efficient technologies; EC, emission reduction with carbon trading; ER, emission reduction without trading; ET, emission reduction with commodity trading.

energy systems. This process represents the degree to which base year capital stocks turn over and affect the future capital stocks of different technologies.

5. The representation of regional resource bases varies across models. Resource bases are not critical for fossil technologies, as these are globally traded commodities, but they are essential for determining the share of renewable energy sources and CCS technologies. For solar power, for example, some models assume regional production limits, some assume regional supply curves, some CGE models assume a fixed factor, and other models assume no limits. Similar differences in assumptions for other technologies are also present across models. However, each model provides its own representation of the different technologies. For example, GCAM represents solar and wind with supply curves and bioenergy with endogenous land competition. In addition, although there is no limit for CCS supplies, regional resource bases in Japan and South Korea are constrained.
6. Models have different assumptions about restrictions on the trade of fossil fuels and bioenergy. Some models assume no constraints on trade, others include transportation costs, and some CGE models assume Armington trade.
7. Though most models include technology cost as an exogenous assumption, some modeling frameworks, such as WITCH, model technology costs endogenously.
8. Finally, solution algorithms differ across models. Most technology-detailed bottom-up models are based on an intertemporal modeling framework, whereas others, such as GCAM, are myopic and their solution algorithm is recursive dynamic.

6. SUMMARY AND CONCLUSIONS

For this review, data and information about the results of more than 20 different global models have been collected, with a particular emphasis on two rapidly growing countries, China and India. The primary focus is on the cost estimation methods used to establish the information needed to organize models. The global applicability of such models is also discussed in relation to China, Korea, Japan, India, Indonesia, Europe, Latin America, the MAF, and the United States. The models used include a mix of the different types widely used in bulk assessments of the climate-mitigation costs and emission-reduction benefits within the above regions: Included are top-down, bottom-up, integrative assessment hybrid, backcasting, and simulation models. In addition, we also discuss a model that examines the costs of trading industrial products across the United States, India, and China.

These models provide reports on the drivers of energy demands and emissions: population,

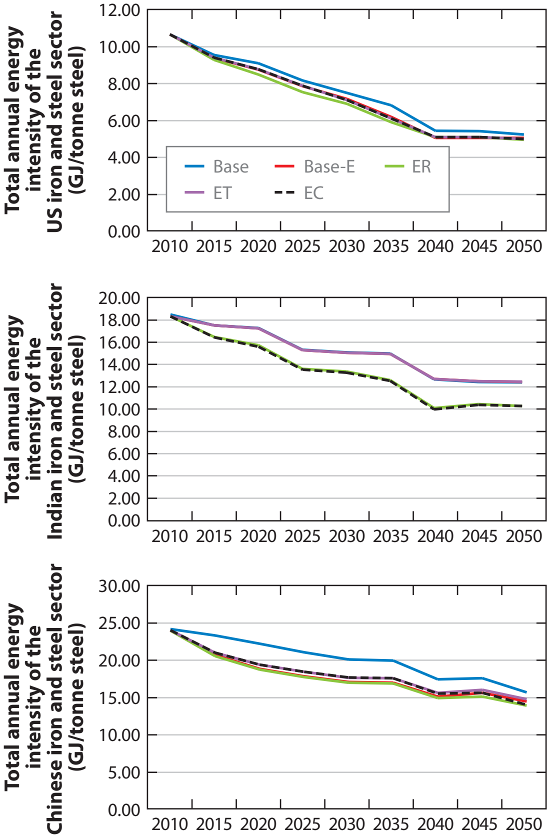

Figure 14

Average energy intensities in gigajoules (GJ) per tonne steel for the iron and steel sector of the United States, India, and China based on predictions from the Base, Base-E, ER, ET, and EC scenarios. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**). Abbreviations: Base, development of the iron and steel sector under current trends; Base-E, the Base scenario plus efficient technologies; EC, emission reduction with carbon trading; ER, emission reduction without trading; ET, emission reduction with commodity trading.

GDP, primary energy, and CO_2 emissions. Whereas the population projections are similar across the models, the values of the latter three drivers are quite different. In this paper, we report primarily on the mean values of all the models and their impacts and benefits for particular regions. Reports show that developing regions (China, India, Latin America, and the MAF) are the primary drivers of global GDP growth: The highest values for China are projected to exceed those of the United States by 8% in 2100. The models show very different primary energy and CO_2 emission projections for China and India. Primary energy use has shown the greatest increase (8.3-fold) in India and is also high in the MAF. The use of fossil fuels is also high, but there is significant variation across models. MESSAGE and ReMIND, for example, show strong 49% and 36%, respectively, shares of solar energy, whereas all other models show an average 8%.

The average primary energy consumption reduction was estimated to be 20%: The largest reduction of approximately 46% was in South Korea and the lowest of approximately 8% in Latin America. China, the MAF, and India are three main regions undertaking the bulk of emission reductions because they have the highest emission increases. CCS technology, which is implemented strongly after many years, yields significant increases in emission reduction. Increased shares of nuclear, solar, and wind energy play important roles globally, with stronger penetration in India, South Korea, the United States, Europe, and the MAF.

In general, the results of the ISEEM-IS trading model confirm that the United States, China, and India are all capable of reducing their carbon intensities by applying country-specific energy efficiency measures. For instance, the United States tends to reduce emissions from its iron and steel sector by importing steel instead of investing in domestic efficiency measures. However, even in the ET scenario, in which the cost of imported steel is higher owing to carbon-trading investments in China and India, the United States still reduces its emissions and, hence, prefers to import.

Some clear points emerge from the intermodal comparison exercise. First, no single technology can play a leading role in global emissions mitigation. A suite of technologies including nuclear, renewable, biomass, and CSS is needed to make deep emission cuts possible. Second, though participation of all regions is important, regions where future demographic and economic growth is concentrated (China, India, and the MAF) will share a larger part of this burden, as most energy demands and emissions growth in the Base scenario are concentrated there. Third, to mitigate emissions in the most cost-effective way, different technologies are important for different regions: For example, nuclear and solar are critical in India, whereas wind and biomass CCS are important in Latin America. Fourth, if stringent climate policy targets are to be met, then emission reduction actions need to be undertaken as soon as possible.

Despite these clear points, different models yield varying assumptions about technology characteristics. Some are more optimistic or pessimistic about different technologies: For example, GCAM is more optimistic about CCS and biomass technologies, whereas ReMIND is optimistic about solar technology. Nevertheless, these points emerge across models covering ranges of uncertainty around the future evolution of technologies, thus making the insights more robust and meaningful. Caution, however, is still warranted, as there are several limitations to the models, approaches, and estimates that need to be examined carefully when understanding the results. Uncertainty about technological change, vast data requirements, increasing model complexity, and lack of flexibility and model applicability are important components that researchers must continue to evaluate to improve model outputs. For example, bottom-up and top-down models are both used to assess economic impacts triggered by energy policies. Both are useful and important tools, but they provide different insights. Top-down models are criticized for not capturing details about the energy sector and for under-representing the complex interactions among demand and supply options. Although bottom-up models can address these issues, they often neglect the macroeconomic impacts of energy policies. Using both models, therefore, helps to address key topics of interest to different communities.

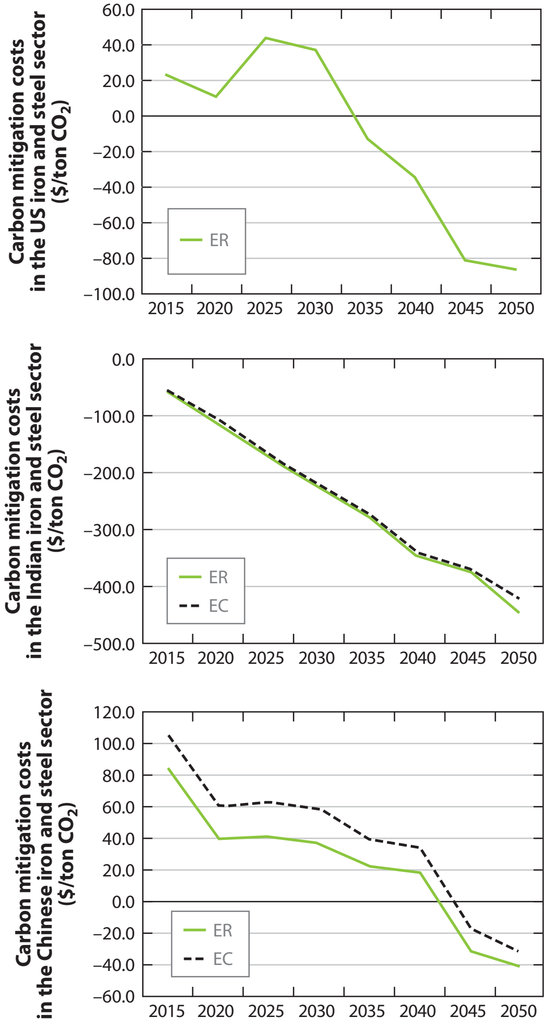

Figure 15

Cost of carbon mitigation in the iron and steel sector in the United States, China, and India based on predictions from the ER and EC scenarios. All data are from Asia modeling exercise (see Reference 34; data are also available at **https://secure.iiasa.ac.at/web-apps/ene/AMEDB/**). Abbreviations: Base, development of the iron and steel sector under current trends; Base-E, the Base scenario plus efficient technologies; EC, emission reduction with carbon trading; ER, emission reduction without trading; ET, emission reduction with commodity trading.

Variations across model structures and key assumptions also yield different results. Large variations about near- and long-term GDP as well as population growth are found across models. Such discrepancies further affect their results about climate benefits and cost impacts. Conversely, variations in cost assumptions require that the modeling team assume similar relative costs in their comparable analyses. Different assumptions about the growth of technologies also significantly impact results. The process of calibrating base year shares represents the degree to which base year capital stocks turn over and affect the future technology capital stocks of different models. In addition, models have different assumptions about restrictions on the trade of fossils and bioenergy. Though most models include technology costs as an exogenous assumption, some frameworks such as WITCH endogenously model technology costs. Finally, solution algorithms differ across models. Most technology-detailed bottom-up models are based on an intertemporal modeling framework, whereas others such as GCAM are myopic and their solution algorithm is recursive dynamic.

Overall, this paper makes a strong effort to collect data for a large number of models and to collate their results in the discussions of baseline and mitigation cases. These results yield interesting global data and show the potential strength of using emission reduction technologies in most regions. The models provide good information for 10 regions with an emphasis on China and India.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The analysis and drafting of this paper were supported by our colleagues in the United States and India. Dr. Nihan Karali, a postdoctoral scientist at the Lawrence Berkeley National Laboratory, provided information and contributed to the writing of the section on the ISEEM energy model for the iron and steel sector. We also acknowledge and thank Dr. Subash Dhar, UNEP RISOE Centre, Denmark, and Dr. Vaibhav Chaturvedi, Joint Global Change Research Institute, USA, for their contributions to the multiple-sector modeling components.

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Annual Review of Environment and Resources

Volume 38, 2013

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Errata

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