Terrestrial ecosystem model studies and their contributions to AsiaFlux

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Abstract

A wide variety of models have been developed and used in studies of land–atmosphere interactions and the carbon cycle, with aims of data integration, sensitivity analysis, interpolation, and extrapolation. This review summarizes the achievements of model studies conducted in Asia, a focal region in the changing Earth system, especially collaborative works with the regional flux measurement network, AsiaFlux. Process-based biogeochemical models have been developed to simulate the carbon cycle, and their accuracy has been verified by comparing with carbon dioxide flux data. The development and use of data-driven (statistical and machine learning) models has further enhanced the utilization of field survey and satellite remote sensing data. Model intercomparison studies were also conducted by using the AsiaFlux dataset for uncertainty analyses and benchmarking. Other types of models, such as cropland models and trace gas emission models, are also briefly reviewed here. Finally, we discuss the present status and remaining issues in data–model integration, regional synthesis, and future projection with the models.

Key words: Atmosphere–ecosystem interactions, Carbon cycle, Eddy-covariance measurement, Micrometeorology, Simulation-based analysis

1. Introduction

Terrestrial ecosystems play important roles in the global biogeochemical cycles and climate system, but these processes and functions have not been adequately quantified. Biophysical exchanges of momentum, heat, and water vapor between the atmosphere and ecosystems affect local micrometeorological conditions, and their coherent actions at broad scales affect meso-scale and eventually global atmospheric dynamics (Raupach, 1991; Bonan, 2002). Terrestrial ecosystems also interact with the atmosphere by exchanging volatile organic gases and particles, which serve as cloud condensation nuclei and react chemically with atmospheric pollutants (Mooney et al., 1987; Arneth et al., 2010). Moreover, ecosystems absorb and release greenhouse gases (GHGs) such as carbon dioxide (CO\textsubscript{2}), methane (CH\textsubscript{4}), nitrous oxide (N\textsubscript{2}O), and ozone in the troposphere (Tian et al., 2016). These functions are garnering attention in terms of anthropogenic climate change and its impacts and mitigation.

These interactions between the atmosphere and ecosystems have been simulated, in early studies, by various kinds of models such as big-leaf models for canopy gas exchange, multi layer models for energy and momentum transfer, and bucket models for surface hydrology in climate models (e.g., Monsi and Saeki, 1953; Manabe, 1969). In particular, micrometeorological studies have led to sophisticated theories on the structure and dynamics of the near-surface atmosphere or boundary layer, providing the basis for land surface models as well as flux measurements (e.g., Obukhov, 1946; Mellor and Yamada, 1974; Monteith, 1977; Sellers et al., 1997; Leuning, 2000; Foken, 2006). The component models (or schemes) have successfully captured target ecosystem processes, which occur mainly at daily or shorter time scales. To capture seasonal, interannual, and decadal ecosystem processes, biogeochemical models that include plant growth and the soil mass budget were developed (e.g., Century by Parton et al., 1988; Terrestrial Ecosystem Model [TEM] by Raich et al., 1991; Forest-BGC by Running and Gower, 1991). These models, which were often constructed on the basis of carbon and nitrogen cycles, have been used to simulate land–atmosphere GHG exchange associated with ecosystem structural change. In light of the increasing attention on global climate change issues, several biogeochemical models have been developed and applied to point- to global-scale simulations. Furthermore, dynamic vegetation models, which simulate temporal change in plant size and/or age structures, have been developed to capture long-term responses to environmental changes (e.g., Lund-Potsdam-Jena [LPJ] by Sitch et al., 2003; Organizing Carbon and Hydrology in Dynamic Ecosystem [ORCHIDEE] by Krinner et al., 2005). At present, these atmosphere–terrestrial models are integrated, so that they can be applicable to short- and long-term simulations (e.g., Joint UK Land Environment Simulator [JULES] by Clark et al., 2011; Community Land Model [CLM] by Lawrence et al., 2019). In general, the models are driven by climate, soil, land-cover and land-use, and atmospheric (e.g., GHG concentration and nitrogen deposition) conditions, and they simulate GHG exchange fluxes and internal biogeochemical processes. Such model integration is also advantageous in including various observations such as flux measurements at a 30-min time step to biomass data at an annual time step (Ito et al., 2015). These models are now being applied not only in scientific research but also to environmental
The models are now playing important roles in environmental and carbon cycle studies with regard to data integration, sensitivity analysis, and future projection (Fig. 1). The development of models is a meaningful way to clarify our knowledge gaps and deepen our understanding of natural processes. In flux research, models are practically useful for temporal gap-filling and spatial upscaling. However, serious uncertainties remain in the ecosystem functions simulated by models, because of complexity and heterogeneity of ecosystems that cannot be formulated and numerically calculated directly. As a result, multiple-model comparison studies have revealed that existing models differ in mean values and environmental responsiveness of ecosystem functions (e.g., Sitch et al., 2008; Ichii et al., 2013). Reducing such uncertainty can be achieved by devising more sophisticated model structure and formulations, and through optimization using observational data. The latter approach includes so-called data assimilation or data-model fusion, in which model parameters (and state variables) are adjusted by minimizing a cost function (Luo and Schimel, 2011). Spatial gaps in observational data, which can reduce data coverage and representativeness, have been largely filled by measurement networks and satellite remote sensing (Kobayashi et al., in preparation). The recent explosive increase of observational data has allowed the adoption of a statistical, data-driven modeling approach. Models based on this approach (e.g., neural network, random forest, support vector regression) do not assume certain physical or biological formulas and parameters and so are more flexible than previous ecosystem models (Reichstein et al., 2019). By applying machine learning algorithms, regional and global continuous fields of heat, water, and CO₂ exchange fluxes have been calculated (Jung et al., 2011; Ichii et al., 2017).

Here, we review model-based studies on terrestrial ecosystems, which have been greatly enhanced by flux measurements — mainly by the eddy-covariance method. Indeed, the evolution of the flux datasets, both in quantity and in quality, from global and regional networks has greatly stimulated modeling studies (e.g., Baldocchi et al., 2001; Friend et al., 2007). This review emphasizes collaborative works with the regional flux measurement network AsiaFlux (Yamamoto et al., 2005; Mizoguchi et al., 2009; Saigusa et al., 2013) and component national networks (e.g., ChinaFlux, JapanFlux, and KoFlux). We summarize the achievements in the development of biogeochemical (process-based) and statistical (data-driven) models and their applications in the Asian region. Numerous global-scale modeling studies have been conducted, and this regional review also refers to several of these key works. Finally, we discuss the remaining research gaps and prospective future directions.

2. Leaf- and Canopy-Scale Models

Models at the leaf and canopy scale aim chiefly at simulating atmosphere–vegetation exchanges of vapor and CO₂ such as gross primary production (GPP) and net ecosystem exchange (NEE), which are regulated by canopy structure and leaf stomatal conductance. Models at these scales are mostly applied to phenomena with short-term (i.e., seconds to days) variability and based on observational data. The canopy photosynthesis model developed by Monsi and Saeki (1953) is a classic example that provided a theoretical basis of canopy radiation absorption on the basis of field observations conducted by using the stratified clip method. This study also proposed the concept of the optimal leaf area index (LAI), providing insights for subsequent studies on canopy structure and resource allocation. Based on micrometeorological insights, Monteith (1972, 1977) established a relationship between canopy-absorbed solar radiation and dry-matter production in forest and cropland, leading to a light-use efficiency (LUE) model that provided a basis for remote-sensing of vegetation productivity. Modeling of leaf gas exchange was markedly improved by the landmark work of Farquhar et al. (1980), who proposed a biochemical and practical photosynthesis model. Later advancements in plant ecophysiology allowed for refinements of the canopy photosynthesis model (Terashima and Hikosaka, 1995). For example, separation of

![Fig. 1. Schematic diagram of the roles of models in atmosphere-ecosystem flux studies. OSSE: Observation System Simulator Experiment; IPCC: Intergovernmental Panel on Climate Change; IPBES: Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services; SDGs: Sustainable Development Goals; GCP: Global Carbon Project; RECCAP: REgional Carbon Cycle Assessment and Processes.](image-url)
beam and diffuse components and inclusion of the within-canopy gradient of leaf nitrogen concentration helps optimize the canopy photosynthesis rate under changing light conditions (de Purry and Farquhar, 1997; Hikosaka, 2014).

Micrometeorological studies have revealed fine-scale structures and dynamics of canopy exchanges of energy and materials (e.g., Inoue, 1963; Monteith, 1964). To capture these processes, multi-layer canopy models have been developed (e.g., Baldocchi and Hutchinson, 1986; Wang and Jarvis, 1990; Leuning, 2000). For example, Tanaka (2002) developed a multi-layer canopy model of CO₂ and water vapor exchange (50 layers) and applied it to a temperate forest in Japan. Kosugi et al. (2006) used a revised version of the Tanaka (2002) model to assess the impacts of leaf physiological variations on canopy gas exchange. In addition, Kumagai et al. (2006) modified the radiation transfer scheme proposed by Tanaka (2002) and developed a multi-layer canopy model applicable to tropical rain forest. The model accurately captures the diurnal variations in heat and CO₂ exchange measured by the eddy-covariance method. To analyze rice canopy processes, Oue (2001) developed a multilayer energy budget model on the basis of a core scheme by Kondo and Watanabe (1992) and investigated the effects of solar angle, plant area density, and stomatal resistance.

Stomatal conductance (and resistance) is a key parameter for the gas exchange models and also for process-based and vegetation dynamics models. Jarvis (1976) proposed the first empirical model of stomatal conductance as a function of light, temperature, humidity, leaf water potential, and ambient CO₂ concentration. Ball et al. (1987) proposed a semi-empirical model, which accounts for interaction between photosynthesis and stomatal conductance. Leuning (1995) modified the Ball et al. (1987) model by considering vapor pressure deficit and intercellular CO₂ concentration as well. The stomatal conductance models have been widely used in analytical and modeling studies conducted in Asia (e.g., Kosugi et al., 2003). Stand-level stomatal conductance may also be estimated on the basis of sap flow measurement data (Kumagai et al., 2008; Yoshifuji et al., 2020). Recent ecophysiological studies proposed new stomatal conductance models (Medlyn et al., 2011; Buckley and Mott, 2013), although more work is needed to evaluate their implementation.

Because of the importance of stomatal regulation on gas exchange, most land-surface schemes used in climate models incorporate some canopy photosynthetic model (Sellers et al., 1997). Mabuchi et al. (1997) developed the Biosphere–Atmosphere Interaction Model (BAIM), which was coupled with a climate model of the Japan Meteorological Agency. The BAIM model has a two-layer vegetation canopy, which accounts for gas exchange regulated by stomatal conductance. Mabuchi et al. (2005) assessed the impacts of vegetation change (e.g., deforestation) on the climate system in the Asian tropical region. Similarly, Takata et al. (2003) developed Minimal Advanced Treatments of Surface Interaction and RunOff (MATSIRO), which is coupled with a climate model of the University of Tokyo and Japan Agency for Marine-Earth Science and Technology. The MATSIRO model has a similar vegetation canopy, which is subdivided into snow-free and snow-covered fractions. Although these land-surface schemes do not put much emphasis on the accuracy of the carbon cycle, they are expected to accurately capture energy and water exchange over the canopy, which is physiologically and inevitably coupled with photosynthesis.

3. Process-Based Models

Process-based or mechanistic models aim to simulate biogeochemical cycles within ecosystems, as well as exchanges with the atmosphere. Typically, this kind of model is used to capture the carbon cycle over interannual and decadal periods, making them effective for analyzing field and flux measurement data. Although several component models (e.g., leaf phenology and soil respiration) have been developed, here we focus on ecosystem-scale flux models. These models were based on ecological studies of primary productivity and carbon stock, many of which were conducted as a part of the International Biological Programme in the 1960s and 1970s. Oikawa (1985) developed an ecosystem-scale carbon cycle model and applied it to an intact tropical rainforest in Pasoh, Malaysia. He analyzed the effects of dry season length and elevated CO₂ concentration on the carbon cycle and thus the stability of the tropical forest. Nakane (1984) developed a soil carbon cycle model and applied it to a pine forest in Hiroshima, Japan. Although these earlier studies provided insights from field data, the models were rather simple (e.g., box-flow model) and operate at annual time steps.

To link flux measurement data with underlying ecophysiology and biogeochemistry, a more mechanistic model was required. Namely, the principal processes of the carbon cycle and associated ecosystem dynamics needed to be described in a theoretical or ecophysiological manner. In addition, models needed to operate daily or shorter time steps in order to be comparable to flux measurements (e.g., 30-min) and capture short-term variability. In contrast, most models of this category do not resolve turbulent transfer processes within the canopy, for simplicity. Ito and Oikawa (2002) developed the Simulation model of Carbon eCYcle in Land Ecosystems (Sim-CYCLE), which simulated the global terrestrial carbon cycle in historical and future periods. The refined model, Vegetation Integrative Simulator for Trace gases (VISIT), was developed by including the nitrogen cycle and trace gas–related processes (Inatomi et al., 2010; Ito, 2010a). One characteristic feature of the VISIT model is its flexible scalability in terms of spatial scale (point to global) and time step (30-min to monthly). The point-scale 30-min-step version was applied to a cool-temperate deciduous broad-leaved forest in Takayama, Japan (Ito et al., 2005) and captured seasonal variability in NEE well. Whereas the early model adopted a “big-leaf” type canopy scheme, a refined model (Ito et al., 2006) introduced a sun/shade type canopy scheme coupled with the biochemical photosynthesis model. This modification, associated with the seasonal change in leaf properties (e.g., leaf mass per area and maximum carboxylation rate), resulted in substantial improvement in the accuracy of GPP and NEE simulation. Ito et al. (2007) also examined the simulation of another CO₂ flux component, ecosystem respiration (RE), and reported poor agreement under stable (i.e., low friction velocity) atmospheric conditions. Inatomi et al. (2010) included CH₄ oxidation and N₂O emission schemes into the VISIT model and evaluated the net GHG budget of a Takayama forest site.
Several models have been developed to simulate the carbon cycle of ecosystems in Asia. Sasai et al. (2005) developed the Biosphere model integrating Eco-physiological And Mechanistic approaches using Satellite data (BEAMS), which is driven by remotely sensed data of the fraction of absorbed photosynthetically active radiation (fAPAR). Sasai et al. (2005) applied the model to seven sites of AmeriFlux, eight sites of EuroFlux, and one site (Manaus) of Large-scale Biosphere–atmosphere experiment in Amazonia, and then Sasai et al. (2007) applied it to the Takayama site. This diagnostic model accurately captured the spatial distribution of GPP over the steep topographic region of central Japan. Sasai et al. (2011) then calibrated the model at five sites in Japan (Teshio, Tomakomai, Takayama conifer, Takayama deciduous, and Seto mixed forest) and at the Laoshan larch site in China to develop a high-resolution East Asian model. Moreover, Sasai et al. (2017) included a CH₄ production scheme into BEAMS and estimated CH₄ emissions from Japanese paddy fields. By focusing on population dynamics and micrometeorological features, Watanabe et al. (2004) developed the Multilayered Integrated Numerical model of Surface physics–Growing plants Interaction (MINoSGI). The model has dynamic vegetation height class and multi layer canopy schemes and explicitly simulates turbulent transport within the canopy. One remarkable feature of the model is the interaction between short-term (canopy fluxes) and long-term (vegetation dynamics) processes. Toda et al. (2007) applied the MINoSGI model to a larch forest and simulated the carbon cycle. Putting further emphasis on vegetation dynamics, Sato et al. (2007) developed the Spatially Explicit Individual-Based Dynamic Global Vegetation Model (SEIB-DGVM), which simulates the global vegetation distribution in the Earth system model. Wu et al. (2019) applied the model to a cool-temperate forest in Tomakomai, Japan, and assessed the impacts of tropical cyclone disturbance on the carbon budget. Focusing on soil carbon dynamics in South Korea, Lee et al. (2014) developed the Korean Forest Soil Carbon (KFSC) model and assessed the net carbon budget of domestic forests. In China, Cao and Woodward (1998) developed the Carbon Exchange between Vegetation, Soil, and the Atmosphere (CEVSA) model, which was primarily used for global studies. Zhang et al. (2012) used a revised version, the CEVSA2 model, to simulate the carbon cycle in a temperate mixed forest in Jilin, China, and conducted a parameter uncertainty analysis.

Many studies have been conducted by using carbon cycle models developed outside Asia. Feng et al. (2007) used the Boreal Ecosystem Productivity Simulator (BEPS), which was originally developed for boreal forests in Canada (Liu et al., 1997), to simulate GPP and net primary productivity (NPP) in China. Tan et al. (2010) used the Organizing Carbon and Hydrology in Dynamic Ecosystem (ORCHIDEE) model, a dynamic global vegetation model developed in France (Krinner et al., 2005), to estimate vegetation biomass and soil carbon stock in the Qinghai–Tibetan grasslands, China. Zhu et al. (2011) used the Integrated Biosphere Simulator (IBIS) developed in the United States to analyze water-use efficiency of terrestrial ecosystems in China, including a future projection under elevated CO₂ concentration. Sun and Mu (2013) used the Lund-Potsdam-Jena (LPJ) dynamic vegetation model, originally developed in Europe (Sitch et al., 2003), to simulate NPP in China under different climate scenarios, implying the importance of climatic perturbations. Ueyama et al. (2010) applied the Biome-BGC model (Thornton et al., 2002), originally developed at a pine forest in Montana, northern United States, to six larch forests in Asia. After parameter calibration, the Biome-BGC model captured the carbon cycle of the forests, allowing them to analyze inter site variations. At black spruce forests in Alaska, Ueyama et al. (2016) also used the Biome-BGC model and attempted to optimize photosynthetic and stomatal parameters using flux measurement data. Kondo et al. (2013) applied the Biome-BGC model at the Takayama, Fujiyoshida, Tomakomai, and Laoshan sites, which differ in forest types and disturbance histories. They demonstrated the effectiveness of flux and biometric (biomass) data to constrain model behaviors across these sites. Focusing on nitrogen dynamics, Shibata et al. (2006) applied the Photosynthesis and EvapoTranspiration (PenET) model (Aber et al., 1995), originally developed in the eastern United States, to a cool-temperate forest in Uryu forest, Japan. They assessed hydrological effects on nitrogen biogeochemistry in conjunction with observational data. Saitoh et al. (2015) applied the National Center of Atmospheric Research Land Surface Model (NCAR-LSM) to the Takayama site and investigated the effects of canopy leaf phenology on the ecosystem carbon budget.

Several process-based models simulate the nitrogen cycle and trace gas emissions of terrestrial ecosystems, in addition to the carbon cycle, because the evaluation of the GHG budget is an important application of the models. Tian et al. (2011) developed the Dynamic Land Ecosystem Model (DLEM) and evaluated the CO₂, CH₄, and N₂O budgets of terrestrial ecosystems in China. Zhu et al. (2016) used the TRIPLEX-GHG model to estimate the CH₄ emissions from Chinese wetlands, including climatic and land-use effects. Using multiple process-based models, Shang et al. (2019) assessed the underlying mechanisms of temporal change in cropland N₂O emissions in China. Ito et al. (2019) conducted a bottom-up assessment of the CH₄ budget in East Asia, using the VISIT model estimations for wetland emission and upland oxidation. Biogenic volatile organic compounds (BVOCs), such as isoprene, are noteworthy because they affect atmospheric quality and climatic conditions and terrestrial ecosystems are a major source of BVOCs. Tanaka et al. (2012) introduced a BVOC scheme, the Model of Emissions of Gases and Aerosols from Nature (MEGAN; Guenther et al., 2012), into MATSIRO and conducted global simulations to assess the impacts of historical climate and land-use changes on BVOC emissions. Situ et al. (2013) also used MEGAN to estimate BVOC emissions in the Pearl River delta region of China and assessed the impacts on surface ozone concentration. Emission factors, however, which are key parameters of the BVOC model have not been well constrained for Asian ecosystems, because of the inadequacy of observational data.

Few model studies have been conducted on wildfire and biomass burning, which is associated with atmospheric emissions of trace gases and particles such as black carbon and carbon monoxide. Most fire-related analyses have been done as a part of global studies (e.g., van der Werf et al., 2010). Considering its biogeochemical importance and increasing social
impact as a disaster, the lack of regional studies on wildfire modeling highlights further research needs and opportunities.

Process-based models are useful for interpreting (i.e., deriving ecophysiological and biogeochemical insights) flux measurement data, which at most sites cover only a few years of variability of a limited number of variables. For example, Ito (2010b) used the VISIT model to interpret the anomalous NEE observed at the Takayama site in 2004 and concluded that it is attributable to the impacts of defoliation caused by tropical cyclones. Adachi et al. (2011) used the same model at a tropical site in Pasoh, Malaysia, and assessed the decadal-scale impacts of land-use conversion to oil palm plantations on the carbon budget and CO$_2$ exchange. Hirata et al. (2014) also applied the VISIT model to interpret the 12-year long change in NEE at the Tomakomai and Teshio forest sites in northern Japan in relation to logging disturbance and management. Kondo et al. (2015a) used the Biome-BGC model to analyze the impacts of anomalous (i.e., associated with El Niño event) meteorological conditions on the carbon budget of the Takayama site through the changes in carbon allocation.

4. Data-Driven Models

The accumulation of flux measurement data and recent development of machine learning algorithms has enabled researchers to develop data-driven (or empirical) modeling and spatial extension of fluxes. Machine learning algorithms such as neural network have been used in flux measurement studies for gap-filling of time series data (e.g., Ooba et al., 2006; Moffat et al., 2007). In addition, empirical or geostatistical algorithms such as Kriging have been used for spatial extrapolation of site-based CO$_2$ fluxes to broad scales (e.g., Saito et al., 2009). Studies have used multiple algorithms not only for temporal gap-filling but also for spatial extrapolation. For example, Papale and Valentini (2003) first applied a machine learning (neural network) algorithm to estimate continental CO$_2$ fluxes using an eddy-covariance observation network focusing on Europe. Furthermore, Yang et al. (2007) applied the support vector regression algorithm to estimate continental GPP across the United States using AmeriFlux data and remote sensing data. Jung et al. (2011) applied the model-tree ensemble algorithm to the FLUXNET dataset and obtained global continuous fields of GPP, RE, and NEE. Although these flux-upscaled maps have several limitations (e.g., short temporal coverage and algorithm-specific biases), they allow us to conduct global observation-based assessments (e.g., Kondo et al., 2015b; Tramontana et al., 2016; Jung et al., 2017). Because of good data availability (frequency, coverage, and variables), the data-driven approach has high affinity with remote sensing. Several studies used carbon cycle models driven by satellite data, such as the Carnegie Ames Stanford Approach (CASAS) model, to assess a regional CO$_2$ budget. Piao et al. (2005) and Pei et al. (2013) used the CASA model to assess the impacts of climate variability and urbanization, respectively, on NPP in China. Ryu et al. (2011) developed a global 1-km resolution mapping model, the Breathing Earth System Simulator (BESS). Instead of machine learning algorithms, BESS considers the radiation budget and photosynthetic (not whole carbon cycle) processes in an explicit manner and is driven by remote sensing data (MODerate resolution Imaging Spectroradiometer [MODIS] Land products).

In this regard, BESS would be a fusion approach between the process-based and data-driven models.

In Asia, Zhu et al. (2014) applied the multivariate regression method to ChinaFlux data (52 sites) and obtained maps of GPP, RE, and NEE across China. Using the region-specific data and model, this study obtained higher GPP in central China than that of the global estimate. L. Zhang et al. (2014) adopted a piecewise regression tree approach for upscaling NEE flux data at 12 sites (including six Coordinated Observation and Synthesis on Arid and Semi-arid China [COSAS]) to temperate grasslands in northern China. This upscaled map allowed them to evaluate the potential of carbon sequestration in the study region. Yao et al. (2018) applied the model-tree ensemble algorithm to up-scaling of flux data obtained from 46 sites in China, including regional data on forest age and nitrogen deposition. Using support vector regression, Ichii et al. (2017) developed flux-upscaled maps of GPP and NEE from 2000 to 2015 based on flux data from 54 sites. As usual for this kind of study, the authors used remote sensing data for data-driven model development (land cover, land surface temperature, LAI, and bidirectional reflectance distribution function-corrected reflectance) and evaluation (GPP, sun-induced chlorophyll fluorescence [SIF], and surface CO$_2$ fluxes). Using the same algorithm, Ueyama et al. (2013) attempted to upscale CO$_2$ flux data obtained at 21 sites in Alaska and obtained regional NEE estimates comparable with those calculated by atmospheric inversion. To clarify the characteristics of machine learning algorithms, Xu et al. (2018) compared five algorithms (neural network, support vector regression, random forest, Cubist based on modified regression tree theory, and deep belief network) at the Heihe River Basin, China. The data-driven modeling approach was also applied to chamber-measured fluxes of soil GHG exchange. Hashimoto et al. (2011) obtained a statistical model of soil GHG exchange (functions of soil temperature, water-filled pore space, and physicochemical properties) on the basis of data from 36 sites in Japan. They applied the model to estimate the total GHG budget of soils in Japan, and Hashimoto et al. (2015) later applied the method to global soils for the period from 1965 to 2012.

The upscaled flux data are effective for assessing broad-scale gradients of ecosystem functions (e.g., Jung et al., 2017; Yu et al., 2019), providing data-driven estimation of terrestrial GPP anomalies responding to extreme climate (e.g., Saigusa et al., 2010), and evaluating process-based models (e.g., Ito et al., 2017). Previous studies indicated, however, that the data-driven algorithms do not work well for NEE and RE, although GPP is captured well by these methods combined with remote sensing data. Although the current algorithms are also not good at upscaling fluxes in disturbed ecosystems or managed croplands, future developments are expected to provide more accurate datasets.

5. Data Assimilation

Data assimilation or data-model fusion is a more advanced use of observational data than conventional comparison for validation (Wang et al., 2009). The concept and methods were developed earlier for atmospheric and ocean models, aiming at improving reliability of numerical weather forecast (Navon, 2009). In the early stage of data assimilation with carbon cycle and
ecosystem models, Kaminski et al. (2002) attempted to assimilate atmospheric CO₂ concentration data to the Simple Diagnostic Biosphere Model (SDBM). Because the model was coupled with an atmospheric transport model, a numerical algorithm — the adjoint method — was applicable to their system, later called Carbon Cycle Data Assimilation System (CCDAS). Kato et al. (2013) applied the system to a semi-arid woodland site in Botswana by using satellite (MODIS fAPAR) and flux measurement data. At the global scale, Chen et al. (2017) developed the Global Carbon Assimilation System (GCAS), in which the BEPS model was optimized with the adjoint algorithm and ground-observed CO₂ data. Ju et al. (2010) used another popular data-assimilation algorithm, the ensemble Kalman Filter, to optimize the BEPS model at a subtropical coniferous plantation at the Qianyanzhou site in China. While using a non-linear data assimilation algorithm (Particle Filter), Arakida et al. (2017) attempted to assimilate satellite-observed LAI to the SEIB-DGVM. By optimizing two parameters (maximum photosynthesis and leaf dormancy start date), they obtained better accuracy in capturing stand LAI seasonality. Ise et al. (2018) applied the Particle Filter to the Super-Simple Stochastic Ecosystem Model (SSSEM) at the regional (i.e. all of Japan) scale; optimization of leaf onset and offset threshold temperatures improved the accuracy of simulated leaf phenology. Several studies estimated terrestrial CO₂ budgets by assimilating atmospheric measurement data. For example, H.F. Zhang et al. (2014) used the CarbonTracker Data Assimilation System (CTDAS) to estimate the net carbon budget of China in 2001–2010.

6. Model Intercomparison

Comparison of the simulation results of multiple models, using common forcing data and protocol, have been done for (1) the evaluation of the range of estimation uncertainty, (2) specification of sensitive processes and parameters, and (3) extraction of consistent patterns. Benchmarking is a kind of model intercomparison that chiefly focuses on the agreement with a particular observational dataset. Many model intercomparison projects have been conducted to assess the range of estimation uncertainty, especially at the global scale, for which observational data are generally sparse and inadequate (e.g., Cramer et al., 1999; Sitch et al., 2008; Tian et al., 2015). Furthermore, comparison between different approaches provides addition insights. For example, Jiang and Ryu (2016) compared GPP and evapotranspiration derived from a process-based model (BESS), a data-driven model with FLUXNET data, and a semi-empirical LUE model with remote sensing (MODIS).

Regional model intercomparison projects have also been done, including in-depth analyses on some region-specific features. Piao et al. (2011) used three models (ORCHIDEE, LPJ, and SDGVM) to evaluate the influence of climate, land-use, ozone, and agricultural management on the terrestrial carbon budget in East Asia. Although the results showed a complicated pattern, this work demonstrated the effectiveness of this modeling approach. Ichii et al. (2010) conducted a comparison of nine data-driven and process-based models: support vector regression, TOPS, CASA, VISIT, Biome-BGC, DAYCENT, SEIB, LPJ, and TRIFFID; comparison of simulated values with flux measurement data of monthly GPP, RE, and NEE was conducted at four forest sites in Japan (Teshio, Tomakomai, Takayama, and Fujiyoshida). This study also compared the results of spatial simulations across Japan and confirmed the effectiveness of parameter calibration at flux measurement sites to reduce estimation uncertainty. As a part of the same project, Ito et al. (2010) compared the simulation results of soil respiration, for which many chamber measurement data were available. Ichii et al. (2013) expanded the study area to East Asia and compared the simulation results of eight models (BEAMS, CASA, Biome-BGC, CLM3.5-CN, PnET-CN, VISIT, LPJ, and MOSES2/TRIFFID) at 24 sites in the AsiaFlux network covering a variety of ecosystems (Fig. 2). The results revealed large inconsistency and estimation uncertainty in the present model performance at tropical rainforest sites. At a larch forest in eastern Siberia, Takata et al. (2017) conducted an intercomparison among process-based, data-driven, and top-down (atmospheric inversion, mentioned later) models and assessed the temporal variability and scale-dependency of simulation consistency.

Regional analyses using global simulation results have been conducted. Sitch et al. (2008) started the TRENDY project, which aims at analyzing dynamic global vegetation models, and the datasets have been widely used for analyses. Kondo et al. (2018) used the simulated net biome production of the TRENDY dataset for an analysis of the carbon budget of Southeast Asia. This study highlighted the remarkable impact of land-use change on the long-term carbon budget and climatic impacts on interannual variability in the region. Piao et al. (2012) used the TRENDY dataset extracted for East Asia as a part of the Regional Carbon Cycle Assessment and Processes (RECCAP; Sitch et al., 2015). Model-ensemble results are useful for achieving a consistent regional carbon budget, compensating for the eddy-covariance flux measurement data (Jung et al., 2011). Recent advancements in the data-driven approach have allowed us to use the upscaled flux data for model benchmarking. For example, Ito et al. (2017) used the global GPP data upscaled from the FLUXNET data and investigated agreements among eight terrestrial process-based models that participated in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP).

7. Regional Synthesis of Carbon Budget

Modelling is playing an important role in the global and regional synthesis of carbon budgets, through collaborations with other approaches. As mentioned above, process-based and data-driven models provide estimates of terrestrial CO₂ budgets that are necessary for bottom-up evaluations, such as East Asia by Piao et al. (2012), South Asia by Patra et al. (2013), and Southeast Asia by Kondo et al. (2018). Ito (2008) and Yoo et al. (2013) applied the VISIT model to East Asian and South Korean land areas, respectively, and evaluated the regional ecosystem CO₂ budget. Recently, Yun et al. (2020) assessed the temporal changes (e.g., enhanced ecosystem uptake) in CO₂ budget of South Korea using atmospheric CO₂ measurement data, process-based models, and atmospheric transport models.

In broad-scale synthesizes, remote sensing plays an increasingly indispensable role, and the collaboration of field measurement, modeling, and remote sensing provides plenty of research opportunities. For example, global continuous maps of fAPAR, LAI, and GPP compiled using multiple platforms and processing
algorithms are available (e.g., Zhao et al., 2006; Yuan et al., 2011; Zhu et al., 2013). Continuous measurements of these variables provide data on temperate phenology and its interannual variability under monsoon climate (e.g., Nasahara and Nagai, 2015). Broad-scale measurements with lidar, e.g., for canopy height, leaf-area density, and vegetation optical depth, allow us to assess structural aspects of terrestrial ecosystems (e.g., Hosoi and Omasa, 2009; Ma et al., 2014; Itakura and Hosoi, 2019; Liu et al., 2019).

Recently developed fine-resolution spectrometers allow the measurement of SIF, which is more tightly coupled with photosynthetic biochemistry than simple reflectance. As demonstrated by Ito et al. (2017), emitted SIF intensity data are useful for examining spatial and temporal variability of GPP simulated by process-based models. These satellite data are obviously useful for data-driven models (e.g., Ichii et al., 2017). Moreover, global GPP data calculated from satellite-observed SIF have become available for more straightforward comparison with the results of process-based models (Li and Xiao, 2019). In Asia, many SIF-oriented field and model studies have been conducted at different sites and scales. For example, Yang et al. (2018) measured CO₂ flux and SIF at a paddy field of Cheorwon, South Korea, and examined the relationship between SIF-derived light-use efficiency and observed GPP. Based on field works, Dechant et al. (2020) presented a framework for analyzing the SIF–GPP relationship in terms of canopy physiological and structural factors for different crops. Although vegetation structure and associated radiation transfer within canopy make the relationship complicated, intimate field–satellite–modeling collaborations would enable us to quantify canopy photosynthesis with higher accuracy.

Remote sensing studies also provide estimates of regional

**Fig. 2.** Comparison of monthly net ecosystem exchange (NEE) between model simulations and observations at 24 AsiaFlux sites. Reproduced from Ichii et al. (2013). TUR: Tura; YLF: Yakutsk, larch; SKT: Southern Khentei Taiga; LSH: Laoshan; CBS: Changbaishan; MMF: Moshiri, mixed forest; TMK: Tomakomai; TSE: Teshio; GDK: Gwangneung; SMF: Seto; YPF: Yakutsk, pine; TKC: Takayama, conifer; MBF: Moshiri, birch; TKY: Takayama, deciduous; QYZ: Qianyanzhou; HBG: Haibei; BNS: Xishuangbanna; SKR: Sakaerat; MSL: Mase; QHB: Qinghai; MKL: Maeklong; PDF: Palangkaraya; HFK, Haenam; YCS: Yucheng.
carbon budgets by top-down approaches. Several satellites, including the Greenhouse gas Observation SATellite (GOSAT) series of Japan and the Orbiting Carbon Observatory (OCO) series of the United States, provide global data of atmospheric-column CO₂ concentration. By using atmospheric transport models, surface CO₂ exchange fluxes can be inversely estimated from the observed atmospheric CO₂ data (e.g., Maksyutov et al., 2013). Using GOSAT and passenger aircraft measurement data, Basu et al. (2014) estimated the terrestrial CO₂ exchange and its seasonality in tropical Asia. Thompson et al. (2016) assessed the carbon budget of Asia using seven atmospheric transport models and reported a substantial net terrestrial sink on average, 0.46 Pg C yr⁻¹, 1996–2012, mostly in East Asia. The agreement and inconsistency between the bottom-up and top-down estimates have implications for our ability to quantify regional carbon budget with high credibility. Indeed, both approaches are contributing to synthesis of the global CO₂ budget (Friedlingstein et al., 2019). Kondo et al. (2020) investigated the inconsistency i.e., higher land uptake by the top-down approach between the approaches and noted the importance of riverine carbon export to account for the global carbon budget. In sum, to obtain reliable estimates of regional carbon budget, we should use multiple approaches that have different advantages and disadvantages. For example, Fig. 3 compares the annual GPP estimates by using different approaches, indicating overall consistency but local discrepancies.

In terms of the carbon budget, human activities such as agriculture and wood harvest have considerable influences, but their quantification is difficult at the regional scale. A number of flux measurement towers were established in croplands (e.g., Mase paddy field in Japan, Haenam farmland site in South Korea, Jiangdu cropland site in China). However, most process-based models lack realistic agricultural processes such as planting, harvesting, fertilization, and irrigation, and therefore comparison with flux measurement data is difficult in croplands. Instead, several cropland models have been developed to simulate carbon and nitrogen cycles and emissions of GHGs. Fumoto et al. (2008) revised the DeNitrification–DeComposition (DNDC) model to be applicable to paddy fields, by explicitly including rice tilling, the root exudation of carbon and oxygen, and the chemical conditions that lead to GHG production. Katayanagi et al. (2017) applied the model DNDC-Rice to paddy fields in Japan and evaluated CH₄ emissions. Masutomi et al. (2016) developed a paddy field process model, MACRO-Rice, on the basis of the MATSIRO land surface model. Analysis of the model at a paddy field in Tsukuba, Japan, showed that it captured various properties spanning from energy fluxes to grain yield well. Li et al. (2007) developed the Water and Nitrogen Management Model (WNMM) and simulated the nitrogen cycle in a cropland at the Fengqiu Agricultural Experimental Station, China. They found that the model accurately captured the emissions of ammonia and N₂O.

![Figure 3](image URL) Annual GPP (2001–2015 mean) in Asia estimated by different methods. (a) Up-scaled flux measurement data (FLUXCOM: Jung et al., 2017); (b) support vector regression (Ichii et al., 2017); (c) mixed remote sensing and process-based model (BESS v2: Jiang and Ryu, 2016); (d) satellite remote sensing for vegetation reflectance (MODIS: Zhao et al., 2006); (e) satellite remote sensing of sun-induced chlorophyll fluorescence (GOSIF; Li and Xiao, 2019); and (f) process-based model (VISIT; Ito, 2019). Note that two machine learning results (a and b) differ in the observational data used to develop the models.
(2014) compared the results of N₂O emissions at paddy fields in China simulated by WNMM, DAYCENT, and Crop-DNDC. With respect to forest management, Zhao et al. (2009) used the Physiological Principles in Predicting Growth (3-PG) model to simulate the growth of a Chinese fir plantation, including a sensitivity analysis of physiological parameters. Saitoh et al. (2012) applied the NCAR LSM model to an even-aged cypress plantation in Japan and simulated GPP, RE, and NEE. However, few model studies have been conducted including realistic forest management options such as thinning, pruning, and understory mowing.

8. Future Projections

One important purpose of terrestrial ecosystem models is to make future projections, typically in the 21st century. Indeed, many studies have been conducted to assess the impacts of future land-use and climate change on global terrestrial ecosystems (e.g., Friend et al., 2014; Nishina et al., 2014). The future projections are also conducted using Earth system models, in which a carbon cycle scheme is coupled with climatic schemes, aiming at evaluating climatic feedbacks caused by terrestrial and ocean CO₂ exchange (e.g., Hajima et al., 2014). Site-scale future projection is important in terms of early detection of ecosystem changes and their attribution. Ito (2010a) conducted a future projection of the carbon cycle at the Takayama, Tomakomai, and Fujiyoshida sites using the VISIT model and climate scenarios until 2050, and the findings indicated consistent but site- and scenario-dependent increases of GPP and NEE. Regional-scale future projections have also been conducted. For example, Ito et al. (2016) assessed the future changes in NPP, vegetation biomass, and soil carbon stock by the end of the 21st century, using the ISIMIP simulation dataset. As a result of elevated CO₂ and intensified monsoonal climate, the analysis indicated a consistent increase of regional NPP and biomass, with a wide range of variability between models and scenarios. As shown in Fig. 4, considerable changes in the terrestrial carbon budget (e.g., productivity and seasonality) are expected to occur around the AsiaFlux sites, suggesting the importance of monitoring these parameters. Kuribayashi et al. (2017) conducted a future projection for central Japan with the VISIT model. They used future meteorological scenarios produced with a meso-scale meteorological model, Weather Research and Forecast (WRF), accounting for the topographic complexity (e.g., heterogeneous snow cover on the mountain slopes) of the mountainous area. Yi et al. (2019) applied the dynamic soil organic version of the terrestrial ecosystem model (DOS-TEM), originally developed in the United States, to estimate the carbon dynamics of alpine grasslands in Qinghai-Tibetan Plateau under the future-projected climates. They found that the disappearance of permafrost would have substantial impacts on carbon stock and productivity, which were predicted to increase due to the CO₂ fertilization. Ito et al. (2015) conducted a simulation with the NCAR LSM under future (2068–2073) conditions at the Takayama site. These site-scale studies were effective at specifying ecophysiological processes and factors such as changes in leaf phenology and overstory/understory contributions.

9. Concluding Remarks

This review summarized the achievements of model studies conducted in Asia, focusing on relationships with the regional flux measurement network, AsiaFlux. Activities of modeling studies in this region are comparable with those in other regions such as the AmeriFlux and European flux networks (followed by the International Carbon Observation System) (Keenan et al., 2019; Baldocchi, 2020). Many models, including process-based and data-driven models, have been developed in Asia, which is predicted to undergo severe population and land-use pressures. The model studies were enhanced by the use of observational data and have made contributed to the global synthesis of GHG budgets and thereby to policy-relevant activities such as the Intergovernmental Panel on Climate Change assessments and the United Nations Framework Convention of Climate Change (e.g., Saunois et al., 2017; Friedlingstein et al., 2019; Tian et al., 2019). This region is also remarkable for its

Fig. 4. Simulated net primary production (NPP) and net ecosystem CO₂ exchange (NEE) at AsiaFlux sites. (a) Haibei, China; (b) Takayama, Japan; (c) Belut, India; and (d) Pasoh, Malaysia. Based on simulations by seven ecosystem models. Reproduced from Ito et al. (2016).
contributions to the global biogeochemical cycles and climate system. Recent scientific and technological developments (e.g., high-spatial-resolution or geostationary satellites, deep learning algorithms, and high-performance computers) have enhanced environmental modeling studies. Indeed, these models are increasingly necessary not only for scientific studies but also for practical, policy-relevant issues such as impact assessments and management planning (cf. Fig 1). For any of these purposes, validation with flux measurement data from site to global (i.e., upscaled) scales is now necessary to prove that the model is valid.

The increasing utility of models in turn encourages field monitoring and data management as conducted by FLUXNET and AsiaFlux. However, there remain serious issues and uncertainties in the present models of terrestrial processes. As shown by model intercomparison studies, the present models do not agree very well in temporal and spatial patterns in the simulated fluxes, and the increasing complexity of the models makes it more and more difficult to specify pivotal processes and parameters. The present models also have weaknesses in simulating the impacts of extreme meteorological events (e.g., tropical cyclones) and disturbances such as land-use conversion (e.g., from tropical forest to oil palm plantation). Socioeconomic scenarios and climate projections suggest the future intensification of land-use and extreme events, indicating the need for further studies.

Acknowledgements

This study was supported by funds provided by a Japan Society for the Promotion of Science KAKENHI grant (no. 17H01867), the Environmental Research Fund (JPMERF20172010) of the Ministry of Environment, and the Environmental Restoration and Conservation Agency, Japan. This work is a contribution of the AsiaFlux 20th Anniversary, and the authors express their gratitude to all flux researchers whose work is discussed in this review.

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